Entropy: A Stealth Measure of Agency in Learning Environments

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ABSTRACT

This study investigates variations in how users exert agency and control over their choice patterns within the game-based ITS, iSTART-2, and how these individual differences relate to performance. Seventy-six college students interacted freely with iSTART-2 for approximately 2 hours. The current work captures and classifies variations in students' behavior patterns using three novel statistical techniques. Random walk analyses, Euclidean distances, and Entropy measures indicated that students who interacted exhibiting more controlled and systematic patterns demonstrated higher quality strategy performance compared to students who interacted with the system in more disordered fashions. These results highlight the potential for dynamical analyses as stealth assessments indicative of students' degree of agency within adaptive learning environments.

Keywords

Intelligent Tutoring Systems, dynamical analysis, agency, strategy performance, game-based learning, stealth assessment

1. INTRODUCTION

Adaptive environments often incorporate various elements (e.g., customization, games) that promote user control as a means to enhance motivation, performance, and learning outcomes [1-2]. When users take control and exert influence (e.g., through choices) over their situation or environment, they are said to have a strong feeling of agency [3]. Agency has been shown to be a critical component of students' engagement and subsequent learning of academic material. Indeed, it is a widely accepted belief in the classroom that giving students control promotes their motivation and subsequent learning [4].

Many game-based learning environments are designed to further enhance users' feeling of agency. Games allow individuals to exert influence over the learning environment by leveraging the mechanics and features found in popular, non-educational video games [11]. For instance, well-designed games frequently present players with interesting choices, leading to increased engagement and persistence [5]. These games also frequently allow players to customize the visual appearance of the features (e.g., player's avatar in World of Warcraft), which has been associated with increased immersion and intention to replay a game [6]. By adding these elements of agency throughout game-based systems, researchers attempt to increase engagement and enjoyment, and indirectly improve learning outcomes [7].

Despite these theoretical and design considerations, research suggests that individuals vary in their ability to exert control over their environment [8]. These behavioral variations, however, are often hard to capture. One proposed way to measure individual differences in controlled behavior is through the use of dynamical analysis techniques. These methodologies focus on the fine-grained and complex behaviors that emerge over time. Dynamical methodologies focus on time as the critical variable, thus offering scientists a unique means of classifying variation in students' behavior patterns when they are given agency within an adaptive system. These methodologies have previously been used to investigate nuanced and fine-grained behavior patterns within various adaptive systems [10].

The work presented here builds upon previous research by employing three novel dynamical methodologies to act as a stealth measure of how variations in behavioral patterns emerge when students are presented with high levels of control (i.e., many choices) within a game-based environment. Although this level of control should lead to high levels of perceived agency for students, some may struggle to exert control over such an open environment. In this study, we examine how students interact with the game-based system iSTART-2, in concert with subsequent learning outcomes associated with those behavior patterns.

The Interactive Strategy Training for Active Reading and Thinking-2 (iSTART-2) system was designed to improve students' reading comprehension by providing them with strategy instruction [11]. More specifically, the iSTART-2 system trains students to use self-explanation strategies while reading challenging science texts. This system has been shown to improve students' reading comprehension ability [11].

iSTART-2 utilizes a game-based environment that was specifically designed to increase students' engagement and persistence, factors that have been shown to positively affect learning [11].

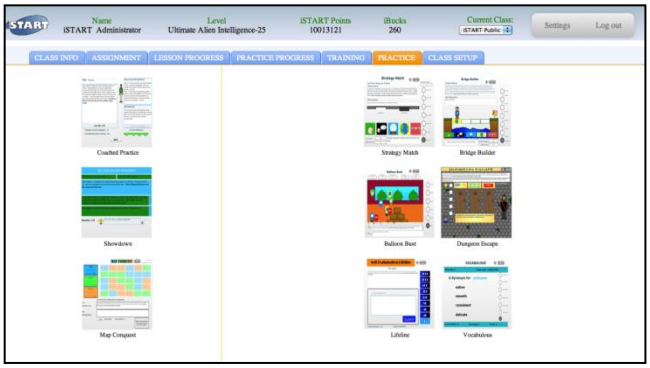

Figure 1. Screen shot of iSTART-2 Selection Menu

The iSTART-2 system consists of two phases: training and practice. Within the training phase, students are introduced to and provided examples of self-explanation strategies. After training, students are transitioned to the practice phase when they are free to interact with the game-based interface embedded within the system (see Figure 1).

There are four types of game-based features within iSTART-2. *Generative practice games* require students to write self-explanations in response to target sentences in science texts. *Identification mini-games* provide example self-explanations and ask students to indicate which previously learned strategy was used to generate the self-explanation. *Personalizable features* allow students to customize the color and appearance of the system interface. *Achievement screens* offer students a summary of their performance levels within the system. In the current study, students were free to interact with these features in any way they saw fit.

The current study uses three novel statistical techniques—random walks, Euclidean distances, and Entropy scores—to categorize nuances in students' choice patterns that emerge while they engage within the iSTART-2 interface. Using these methodologies, we investigated students' choice patterns and the impact of variations in those patterns on learning outcomes (i.e., self-explanation quality) within the context of iSTART-2.

2. METHOD

Participants in the current study included 76 college students who were from a large university campus in the Southwest United States. The students were, on average, 18 years of age, with a mean reported grade level of college freshman. Of the 76 students, 58% were male, 55% were Caucasian, 22% were Asian, 7% were African-American, 10% were Hispanic, and 6% reported other nationalities.

Students in this study completed one 3-hour session that consisted of a pretest, strategy training, game-based practice within iSTART-2, and a posttest. During the pretest, students answered a battery of questions to assess their prior attitudes and motivation. During training, students watched a series of videos that instructed them on various self-explanation strategies and their applications. After training, students were transitioned into the game-based practice portion of the experiment. In this section, students were exposed to the game-based menu within iSTART-2 (see Figure 1) where they were allowed to interact freely within the system interface. Finally, at posttest, students completed a battery of questionnaires similar to those in the pretest.

2.1 Measures

2.1.1 Strategy performance

During game-based practice, students' generated self-explanation quality was measured using the iSTART-2 algorithm, which assigns scores that range from 0 (poor) to 3 (good). This algorithm incorporates both latent semantic analysis (LSA) [12] and word-based measures and has been shown to be reliable and comparable to expert human raters across a variety of texts [for more information see 13].

2.1.2 System Interaction Choices

Within the iSTART-2 system, students can chose to interact with a variety of features that fall into one of the four types of game-based feature categories: *generative practice games, identification mini-games, personalizable features,* and *achievement screens.* All interactions within iSTART-2 were logged by the system and then categorized as one of these four types. Tracking students' choices with these four distinct categories of features allows us to investigate patterns in students' choices across and within each type of interaction.

3. QUANTITATIVE METHODS

To examine variations in students' behavior patterns within iSTART-2, random walks, Euclidean distances and Entropy analyses were conducted to investigate how variations in students' choice patterns impact learning outcomes (i.e., self-explanation quality) within the context of iSTART-2. The following section provides a description and explanation of random walks, Euclidean distance, and Entropy analyses.

Random walks are mathematical tools that provide visualization of patterns that manifest within categorical data across time [14]. In the current study, we used random walks to visualize and capture the fluctuations within students' interaction patterns with iSTART-2 by examining the sequential order of students' interactions with the four types of game-based features (i.e., generative practice games, identification mini-games, personalizable features, and achievement screens). Each of these game-based features was given an assignment along an orthogonal vector in an X, Y scatter plot. These assignments are as follows: generative practice games (-1,0), identification mini-games (0,1), personalizable features (1,0), and achievement screens (0,-1). It is important to note that these vector locations are random and not associated with any qualitative value. This methodology has previously been used to trace students' interaction patterns within the game-based ITS, iSTART-ME [10].

To generate a unique walk for each student, we placed an imaginary particle at the origin (0,0). Then, every time the student chose to interact with a game-based feature, the particle moved in a manner consistent with the vector assignment. The use of these vectors allows us to assign a movement to students' choices within the system. The combination of these movements yields a continual pattern or "walk" for each student's interactions within iSTART-2.

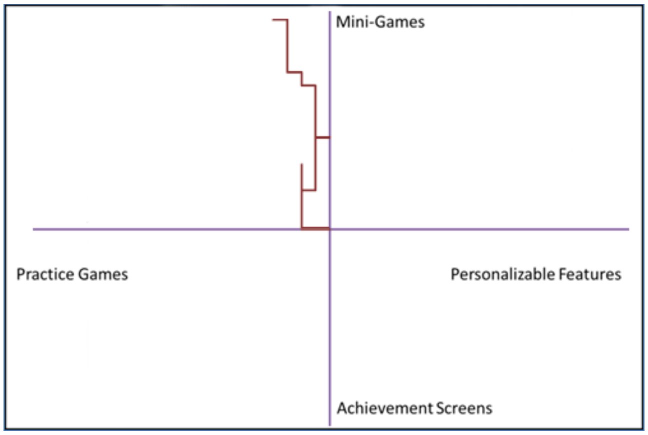

Figure 2. Actual random walk for one participant

Figure 2 is an actual *walk* from the current study. This walk is a visualization of one student's interactions within the system. The trajectory of the walk suggests that this student interacted more frequently with the identification mini-games. Within these random walks, there are fluctuations and nuances that may inform how controlled students' choice patterns were. To understand how students' patterns changed, distance time series were constructed for each student by calculating a measure of Euclidean distance. This calculation was measured from the origin (coordinates 0,0) to each step (see equation 1). Within this equation, y represents the particle's place on the y-axis, x represents the particle's place on the x-axis, and *i* represents the *i*th step within each student's walk:

$$\text{Distance} = \sqrt{(y_i - y_0)^2 + (x_i - x_0)^2} \qquad (1)$$

Euclidean distance was calculated for each step in a student's walk, which produced a distance time series. These distance time series can then be used to reflect the degree to which students controlled their pattern of choices. That is, if students showed a systematic pattern in their walk, the distance time series would have reflected this controlled pattern through coordinated *steps*.

Students' propensity to engage with the system in an ordered fashion was calculated using Entropy [15]. Entropy is a statistical analysis that has previously been used across a variety of domains as a way to measure random, controlled, and ordered processes [16]. Hence, within the current study, Entropy provides a measure of how students' choice patterns reflected controlled versus ordered processes.

Entropy was calculated using the distance time series produced from students' random walks and Euclidean distances (see equation 2). Within Equation 2, $P(x_i)$ represents the probability of a given state. This means that the Entropy for student X is the inverse of the sum of products calculated by multiplying the probability of each achieved state by the natural log of the probability of that state.

$$\text{H(x)=-}\sum_{i=0}^{N} P(x_i)(\log_e P(x_i)) \qquad (2)$$

The Entropy formula in Equation 2, captures the amount of order (or disorder) present in a specific time series. Within the context of the current study, a low Entropy score suggests highly organized choice patterns, whereas high Entropy suggests disorganized choice patterns.

4. RESULTS

4.1 Entropy

This study examined how students' patterns of interactions with game-based features influenced the quality of their generated self-explanation quality. To characterize how students interacted with the system, Entropy was calculated using Euclidean distances generated from each student's unique random walk. These Entropy scores suggested that students varied considerably from controlled to disordered (range =1.32 to 2.32, M=1.83, SD=0.24; skewness = -.22; kurtosis = -1).

4.2 Interaction Choices

To examine the relation between Entropy scores (i.e., measure of order or disorder) and students' frequency of interaction choices, we calculated Pearson correlations. Students' Entropy scores were not significantly related to their frequency of interactions with generative practice games (r=-.14, p=.23), identification mini-games (r=.05, p=.65), personalizable features (r=.03, p=.77), or achievement screen views (r=.09, p=.43). Thus, patterns in students' choices were not related to any specific feature within iSTART-2.

4.3 Learning and System Performance Outcomes

To examine the effects of agency on performance during practice, a median split was performed on students' Entropy scores to profile students according to their patterns of interactions. This median split resulted in the creation of two groups: ordered students (M=1.6, SD=.15) and disordered students (M=2.0, SD=.11). Differences between the ordered and disordered students' self-explanation quality during practice were examined using a one-way ANOVA. This analysis revealed that ordered students generated higher quality self-explanations (M=1.8, SD=.55), compare to disordered students (M=1.6, SD=.44), $F(1,74)$=4.78, p=.03, η^2=.10[1].

A similar one-way ANOVA was used to examine differences between ordered and disordered students' game performance within iSART-2. These results revealed that ordered students also earned significantly more trophies (M=1.4, SD=.22) while playing the practice games than disordered students (M=.6, SD=.09), $F(1,74)$= 9.17, p=.003, η^2=.11. Together, results from both ANOVA analyses indicate that students who engaged in a more ordered behavior pattern showed significantly better game performance relative to students who engaged in a disordered behavior pattern.

5. DISCUSSION

Researchers have argued that enhancing feelings of agency by introducing choice influences students' engagement and ultimately impacts learning outcomes [4]. However, students vary in their ability to effectively control and regulate their behaviors when presented with this freedom [9]. This variability is often missed when researchers use static measures (e.g., self-reports)

[1] Similar trends are found using Entropy as a continuous variable to predict self-explanation quality during practice.

alone. Dynamical analyses offer one way to capture variances in students' ability to control their behaviors when they are presented with additional opportunities to exert agency.

The current study made use of three novel dynamical methodologies by employing random walks, Euclidean distances, and Entropy analyses in an attempt to capture each student's unique interaction pattern within iSTART-2. The current analysis is one of the first to use Entropy as a means to provide a stealth assessment of students' patterns of interactions within a tutoring environment. These scores reveal trends across time that are suggestive of the degree to which students exerted agency within the iSTART-2 system.

Findings from the current analyses fall in line with previous work that has shown that students' ability to regulate and control their learning behaviors has a positive impact on learning outcomes [9]. Students who acted in a more controlled fashion generated higher quality self-explanations during practice. Interestingly, students' controlled patterns of interactions were not related to any specific game-based feature. This indicates that it is not about what students choose to do, but how they choose to do it. Thus, students' ability to effectively control their behaviors when presented with a considerable amount of choice seems to be important for immediate learning outcomes. This is especially important within game-based environments where students are often given considerable control over their learning trajectories [10]. Students who exhibit controlled behaviors are likely to be experiencing and benefitting from strong feelings of agency, as intended by the design of these learning environments.

6. ACKNOWLEDGMENTS

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