Who’s in Control?: Categorizing Nuanced Patterns of Behaviors within a Game-Based Intelligent Tutoring System

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ABSTRACT
The authors use dynamical analyses to investigate the relation between students’ patterns of interactions with various types of game-based features and their daily performance. High school students (n=40) interacted with a game-based intelligent tutoring system across eight sessions. Hurst exponents were calculated based on students’ choice of interactions with four types of game-based features: generative practice, identification mini-games, personalizable features, and achievement screens. These exponents indicate the extent to which students’ interaction patterns with game-based features are random or deterministic (i.e., controlled). Results revealed a positive relation between deterministic behavior patterns and daily performance measures. Further analyses indicated that students’ propensity to interact in a controlled manner varied as a function of their commitment to learning. Overall, these results provide insight into the potential relations between students’ pattern of choices, individual differences in learning commitment, and daily performance in a learning environment.

Keywords
Intelligent Tutoring Systems, dynamical analyses, strategy performance, game-based learning

1. INTRODUCTION
Students’ behaviors during learning tasks vary both as a function of the student and the task. Some students approach learning tasks in a decisive manner, revealing a plan and purpose. These students are controlling and regulating their behavior: a crucial skill for academic success [1 – 6]. However, other students can approach the same task in an impetuous manner, showing little discernible schemes or methods. These students are failing to take control of their own learning behaviors; consequentially, their academic success often suffers [1, 7 – 8]. The emergence of students’ ability to set decisive goals, plans, and make decisions during a task is often referred to as self-regulation [5].

One important component of self-regulation is students’ ability to control their choices and behaviors during learning tasks [8]. To gain a deeper understanding of how self-regulated learning manifests in students’ choices, scientists have begun to examine patterns that emerge in students’ behaviors while they engage with adaptive environments [9 – 10]. These environments produce log data (e.g., keystroke or mouse click data) that are rich in information about what students choose to do while engaged with the system. Analyzing patterns that emerge within log data has been shown to shed light upon the amount of agency exerted during tasks. The utilization of log data is especially useful for researchers interested in examining how students engage with game-based systems, which typically offer students high levels of agency. As students engage with game-based environments, they are frequently provided with multiple choices and trajectories. These variations allow students to exhibit several levels of control, which influence the interaction patterns that manifest during their time within the system. Consequently, these environments provide researchers a unique opportunity to examine students’ ability to control their learning experience and the ultimate impact this skill has on learning outcomes.

The ability to effectively self-regulate is challenging for many students, as they often struggle to set their own learning goals and control their behaviors during learning tasks. As a result, self-regulation skills (e.g., ability to control behaviors) tend to vary widely among students [11]. Thus, it is critical to understand what individual differences drive various interaction patterns that may be indicative of students’ ability to control their behaviors. Historically, individual difference researchers have shown that students vary in the way that they learn and interact in the classroom [12 – 14]. More recently, it has been shown that individual differences, such as expectations of technology, prior reading ability, and commitment to learning, similarly influence students’ interactions and performance within adaptive learning environments [15 – 17].

The current study builds up upon this work by investigating the extent to which students’ patterns of interactions display deterministic and controlled properties, and how those properties ultimately impact daily performance outcomes. Additionally, we investigate whether these interaction patterns vary as a function of individual differences in students’ commitment to learning, prior reading ability, or expectations of technology. By investigating students’ propensity to interact in controlled (i.e., deterministic) patterns within learning environments, our goal is to enhance theoretical understandings of self-regulation and its ultimate impact on learning gains.

1.2 iSTART-ME

The context of this study is iSTART-ME (Interactive Strategy Training for Active Reading and Thinking-Motivationally-Enhanced), a game-based Intelligent Tutoring System (ITS) designed to improve students' reading comprehension skills by providing them with instruction and practice on how to use self-explanation and comprehension strategies [18]. This game-based tutoring system was built upon a traditional ITS (i.e., that was not game-based) called iSTART [19]. iSTART and iSTART-ME are similar in that they both introduce students to self-explanation strategies, demonstrate the use of these strategies, and allow students to practice applying self-explanation strategies to science texts. This scaffolding is conducted in three separate modules (for more detail about these modules and the original iSTART system, please see [20 -21]).

Figure 1. Screen shot of iSTART-ME Selection Menu

iSTART-ME builds upon the original iSTART system by adding in game-based practice. This game-based environment provides an opportunity for extended practice and was designed to enhance students' motivation and persistence during extended training sessions (see Figure 1; [21 -22]). Within this game-based practice environment, students can choose to interact with the interface in a variety of ways, such as reading and self-explaining new texts within the context of a game (see Figure 2 for a screenshot of a generative game), personalizing the system interface, or playing identification mini-games (see Figure 3 for screenshot of a mini-game; for a more detailed description of the iSTART-ME system, please see [18]). iSTART-ME presents students with a variety of activities they can choose from. This flexibility puts iSTART-ME in a unique position to assess the agency exhibited within students' patterns of interactions and how those various patterns ultimately impact learning.

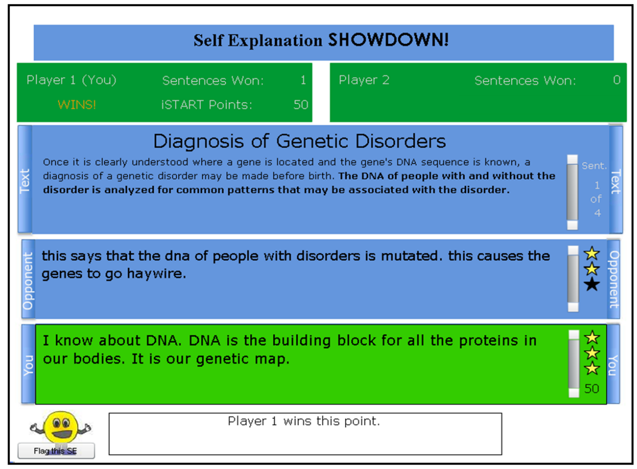

Figure 2. Screen Shot of Generative Practice Showdown

iSTART-ME assesses students' self-explanations through the use of a feedback algorithm [19]. Self-explanations are scored on a scale that ranges from 0 to 3. A score of "0" is assigned to any self-explanation that is composed of irrelevant information or is considered too short. A score of "1" indicates that the self-explanation relates to the sentence but does not elaborate upon the information within the text. A score of "2" is assigned when students' self-explanations incorporate information from other locations in the text beyond the target sentence. Finally, a score of "3" indicates that the self-explanation incorporates information from both the text and students' prior knowledge.

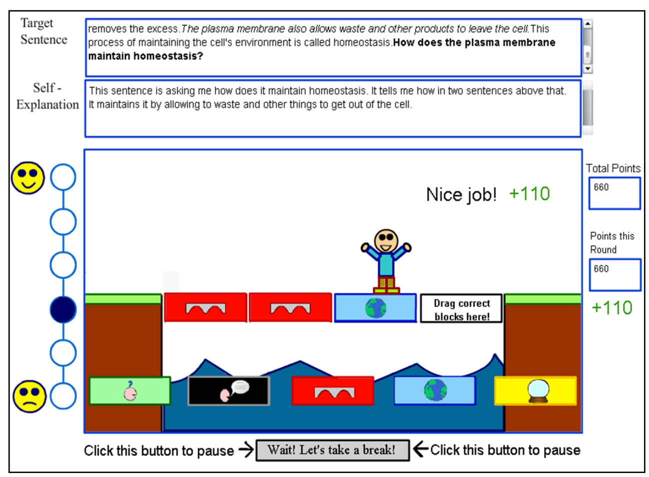

Figure 3. Screenshot of iSTART-ME mini-game Bridge Builder

1.3 Current Study

Previous work has provided insight into the way that individual differences influence how students regulate their behaviors. However, there remain questions regarding the influence of these individual differences on students' behavior patterns and learning outcomes. The current study attempts to address this issue by examining how students' behavior patterns within the game-based environment iSTART-ME relate to system performance and vary as a function of individual differences. We investigated two primary questions:

1) Do students' behavior patterns influence their daily self-explanation quality?
2) Do individual differences influence students' patterns of interactions within the system?

2. METHODS

2.1 Participants

Participants in the current study (n= 40) were high school students from the Midwest United States. The students were, on average, 15.9 years of age, with a mean reported grade level of 10.4. Of the 40 students, 50% were male, 17% were Caucasian, 73% were African-American, and 10% reported other ethnicities.

2.2 Procedure

The current work is part of a larger study conducted to compare iSTART-ME, iSTART, and a non-tutor control [18]. The current study solely focuses on the 40 subjects assigned to the iSTART-ME condition, as they had access to the full game-based environment. The study consisted of 11 sessions. Session 1 was a pretest wherein the students answered a battery of questions, including measures of prior ability, commitment to learning, and attitudes toward technology. During sessions 2 through 9, students interacted with the game-based system. Session 10 comprised the posttest portion of the experiment, including measures similar to those in the pretest. Finally, one week after the posttest, students returned for session 11. During this session, students completed a retention test that included similar measures as the pretest and posttest.

2.3 Measures

2.3.1 Pretest reading comprehension

Students' reading comprehension ability was assessed using the Gates-MacGinitie Reading Test [23]. This test is a well-established measure of student reading comprehension (α=.85-.92 [24]). This task consists of 48 questions that ask students to read a passage and then answer two to six comprehension questions about the material in that passage.

2.3.2 Strategy performance

Students' self-explanation ability was assessed at pretest and during training. At pretest, students were asked to read a short science passage and self-explain predetermined target sentences in that text. During training, students' self-explanation ability was assessed through their interactions with the generative practice games. In these games, students were shown science texts and asked to generate their own self-explanations for various target sentences within the texts. All self-explanations were scored using the previously mentioned iSTART algorithm.

2.3.3 System Interaction Choices

Students' recorded interactions with iSTART-ME involved one of four types of game-based features, each representing a different type of game-based functionality within iSTART-ME. Each interaction was classified as involving one of the four categories of game-based functionalities (see Table 1 for descriptions).

Table 1. Interaction Categories within iSTART-ME

Interaction Classification	Description
Generative Practice	Students generate their own self-explanation
Identification Mini-Games	Students identify the self-explanation strategy
Personalizable Features	Students customize some aspect of the system interface
Achievement Screens	Students view their performance within iSTART-ME

2.3.4 Commitment to Learning

Students' commitment to learning was assessed at pretest through two self-report questions. A composite score was calculated that combined the questions related to students' enjoyment of learning and their frequency of reading for enjoyment (see Table 2 for questions).

Table 2. Learning Commitment Questions

Response Statement	Scale*
"How much do you enjoy reading?"	1 - 6
"How much do you enjoy learning about non-scientific material?"	1 - 6

*1 (Strongly Dislike) to 6 (Strongly Like)

2.3.5 Prior Expectations of Technology

Students' prior expectations of technology were assessed at pretest. This measure was a composite score that combined two self-report measures related to students' expectations of computer helpfulness and their expected enjoyment while interacting with the iSTART-ME system (see Table 3 for questions).

Table 3. Prior Expectations of Technology Questions

Response Statement	Scale*
"Do you expect to enjoy interacting with this system?"	1 - 6
"Do you expect computers to be helpful?"	1 - 6

*1 (Strongly Disagree) to 6 (Strongly Agree)

2.4 Dynamical Methodologies

Students' interaction patterns were classified using two dynamical methodologies. First, students' sequence of interaction patterns were analyzed using a random walk model. This method has been used in previous work to analyze fluctuations in patterns across time [16, 25]. Random walks create a spatial representation of categorical sequences across time. In the current study, we generated a unique walk for each student by first placing an imaginary particle at intersection of the x and y-axes (0,0). Then using system log-data we examined the patterns of interactions in which students engaged and moved the particle in a manner consistent with a simple set of rules (see Table 4). These rules dictated what direction the particle would "step." For instance, if students played an identification mini-game the particle moved one "step" up along the y-axis. If students chose to play a generative practice game, the particle moved one "step" left along the x-axis. When students chose to interact with an achievement screen the particle moved one "step" down along the y-axis. Finally, when students chose to interact with personalizable feature, the particle moved one "step" right along the x-axis. Notably, the direction of movement is arbitrary (i.e., a certain direction is not associated with the quality of the feature). Figure 4 reveals what a completed walk from the current study looked like for a student with 326 interaction choices.

Table 4. Particle movement assignment

Students' Choice of Interaction	Direction of Movement
Generative Practice Games	1 step left along the X-axis
Identification Mini-Games	1 step up along the Y-axis
Personalizable Features	1 step right along the X-Axis
Achievement Screens	1 step down along the Y-axis

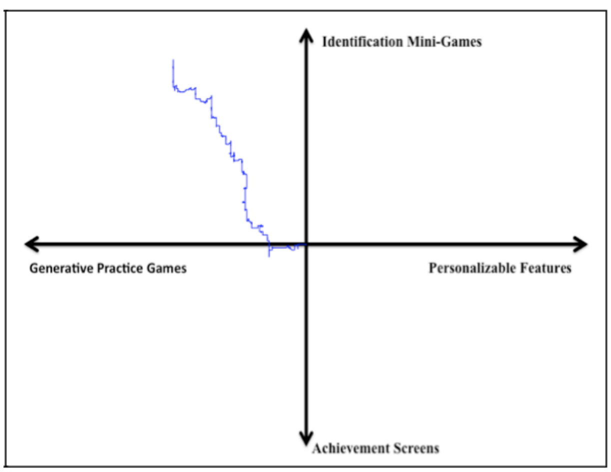

Figure 4. Complete Random Walk

Using students' sequence of categorical choices, we calculated Euclidian distances for each step within their random walk (see Equation 1). The combination of all distance calculations within students' random walk generated a "distance time series." which was representative of the fluctuations in students' interaction patterns across time. These distance time series calculated how far students' choice patterns fluctuated from the origin (0,0). Finally, the classification of each student's interaction pattern was conducted by using the distances time series generated from the random walk analysis and entering them into a detrend fluctuation analyses (DFA). The result of each DFA was a scaling component called the Hurst exponent [26]. The Hurst exponent can classify the tendency of long-term time series as follows: $0.5 < H \leq 1$ indicates persistent (deterministic or controlled) behavior, $H = 0.5$ signifies random (independent) behavior and $0 \leq H < 0.5$ denotes antipersistent (corrective) behavior. Patterns that are classified as persistent are considered to be equivalent to a positive correlation. Time series exhibiting persistence are thought to reflect self-organized and controlled processes [27]. Conversely, when patterns are classified as antipersistent, the pattern is said to be equivalent to negative correlations. This measure has been used in a variety of domains to view fluctuations and the persistence of complex patterns across time [26].

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

3. RESULTS

3.1 Hurst Exponents

Hurst exponents were used to quantify students' patterns of choices within the iSTART-ME system. In the current study students' Hurst exponents varied considerably from weakly to strongly persistent (range =0.57 to 1.00, M=0.77, SD=0.11).

3.2 Hurst Exponents and System Interactions

Within the current study, students varied in the interaction patterns (Hurst exponents). To provide a visualization of what variability in Hurst scores looks like within the system two probability analyses were conducted. These probability analyses are similar to the ones used by D'Mello and colleagues (2007). This calculation can be described as L[It→Xt+1]. Simply put, we are examining the probability of a student's next interaction (X) with an interface feature given their previous interaction (I). For the current study, we calculated two of these probability analyses. One for a student with a high Hurst score (i.e., deterministic pattern) and one for a student with a low Hurst score (i.e., weakly persistent pattern).

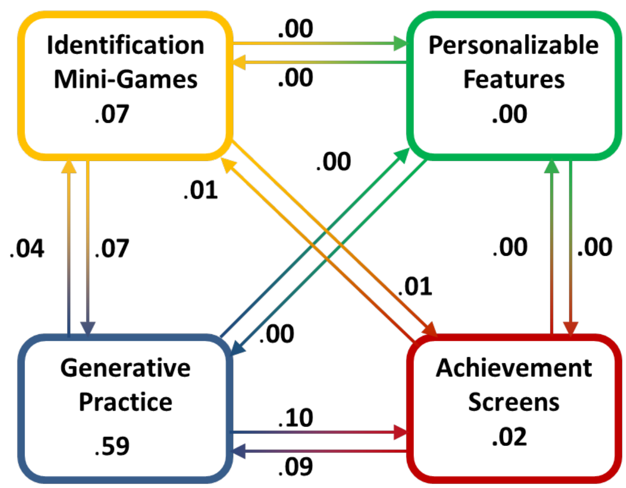

Figure 5. Transitional Probability of a Student with a High Hurst Score

Figure 5 illustrates how a student with a Hurst exponent of .98 interacted with various features in the iSTART-ME system. This student interacted with the generative practice games almost 60% of the time, revealing very little tendency to interact with other features in the system. When this student did engage with another game-based feature, there was a tendency to transition back to the generative practice games afterwards. Thus, this student seemed to be acting in a decisive manner, consistently interacting with generative practice games or transitioning back to generative practice games after engaging with another feature.

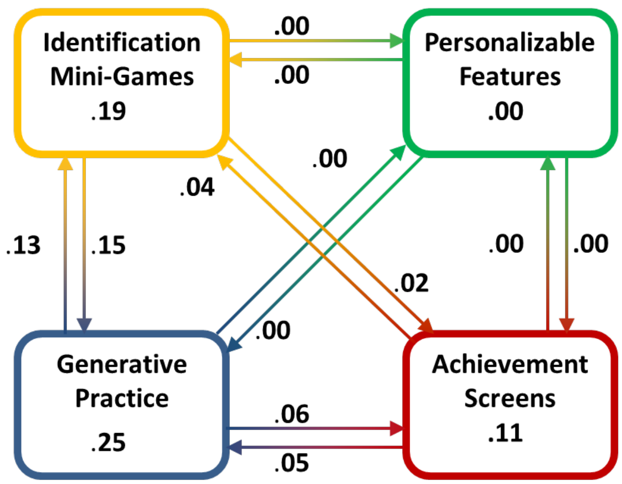

Figure 6. Transitional Probability of a Student with a High Hurst Score

Conversely, Figure 6 illustrates how a student with a Hurst exponent of .60 interacted within the system. This analysis revealed that the student with a low Hurst score explored more of the system interface than the student with a Hurst score of .98 (see Figure 5). However, the interaction pattern was more spread out and less predictable compared to the student with the high Hurst score. Thus, this student was not acting in a decisive manner and as such, may not have been regulating their learning experience within the iSTART-ME system.

3.3 Hurst and Self-Explanation Quality

The current study examined how variations in students' interaction patterns within a game-based environment related to their daily strategy performance. Pearson correlations were conducted (see Table 5) to investigate relations between students' interaction patterns and their daily self-explanation scores. Results from this analysis indicated that there was a positive correlation between students' overall Hurst exponents (regulatory measure) and self-explanation quality on days 1, 2, 3, 4, and 6. Hurst exponents were also marginally related to students' self-explanation quality on days 5 and 7. However, there was no significant relation between Hurst exponents and self-explanation quality on day 8 of training.

To further examine these relations, we conducted separate hierarchal regression analyses on students' self-explanation quality scores for each of the eight training days. These analyses investigated how students' interaction patterns predicted self-explanation scores over and above prior self-explanation ability (i.e., self-explanation scores at pretest). This is reflected by the R^2 change attributable to the variance accounted for by the interaction patterns (i.e., Hurst exponents) after entering prior self-explanation ability in the regression model (see Table 6). These analyses revealed significant models and R^2 change for *session 2*, $F(1,37)=5.32$, $p<.05$, $R^2=.21$, $R^{2Change}=.11$ (i.e., see session 2 in Table 6), *session 3*, $F(1,37)=5.29$, $p<.05$, $R^2=.29$, $R^{2change}=.11$, *session 4*, $F(1,37)=9.42$, $p<.01$, $R^2=29$, $R^{2change}=.19$, and *session 6*, $F(1,37)=6.251$, $p<.05$, $R^2=.19$, $R^{2\ change}=.14$. These analyses also reveal a marginally significant R^2 change on *session 1*, $F(1,37)=3.08$, $p=.08$, $R^2=.41$, $R^{2\ change}=.05$, where prior self-explanation ability accounted for the majority of the variance in performance during that initial session.

Table 5. Hurst Exponents and Daily Self-Explanation Quality

Self-Explanation Quality	Interaction Patterns (Hurst)
Session 1	.325*
Session 2	.387*
Session 3	.391*
Session 4	.477**
Session 5	.296 (M)
Session 6	.405**
Session 7	.282 (M)
Session 8	.054

p=.05*, p<.01**, p<.10 (M)

Table 6. Hierarchal Linear Regressions Predicting Self-explanation Quality from Interaction Patterns (Hurst) and Prior Self-Explanation Ability

Self-Explanation Quality	β	ΔR^2	R^2
Session 1			**.41****
Prior Self-Explanation Ability	.56	.36**	
Interaction Patterns	.23	.05(M)	
Session 2			**.21***
Prior Self-Explanation Ability	.26	.10(M)	
Interaction Patterns	.34	.11*	
Session 3			**.29***
Prior Self-Explanation Ability	.36	.18*	
Interaction Patterns	.32	.11*	
Session 4			**.29***
Prior Self-Explanation Ability	.25	.10(M)	
Interaction Patterns	.43	.19*	
Session 5			**.22***
Prior Self-Explanation Ability	.37	.17*	
Interaction Patterns	.23	.05	
Session 6			**.19***
Prior Self-Explanation Ability	.16	.05	
Interaction Patterns	.38	.14*	
Session 7			**.16***
Prior Self-Explanation Ability	.28	.10(M)	
Interaction Patterns	.25	.06	
Session 8			**.15**
Prior Self-Explanation Ability	.38	.14*	
Interaction Patterns	.04	.01	

p<.05 *, p<.01 **, p<.10 (M)

These findings reveal that students' interaction patterns play an important role in students' daily self-explanation performance, particularly after the first session. We further examined whether students' interaction patterns varied as a function of individual differences using pretest measures of reading ability, commitment to learning, and prior expectations of technology (see Table 7). Results from this analysis revealed that commitment to learning was the only pretest measure significantly related to students' interaction patterns. This variable accounted for 15% of the variance among students' interaction patterns as reflected by the Hurst exponent scores. Indeed, when students reported a higher commitment to learning they were more likely to interact with the system in a controlled and deterministic way. Interestingly, students' prior ability level and expectations of technology was not related to their pattern of interactions. Thus, when given agency over a learning task, students learning goals may be one of the primary factors that influence how regulated they behave. These findings support previous work that shows that students' goals are an important contributor to their ability to self-regulate during learning [29].

Table 7. Correlations between Interaction Patterns (Hurst) and Individual Differences

Variable	Interaction Patterns
Reading Ability	.150
Commitment to Learning	.387*
Prior Expectations of Computers	.281(*M*)

*p < .05, *M*=Marginal

4. DISCUSSION

The current study investigated how students' behaviors within an adaptive environment impacted their daily learning outcomes and varied as a function of individual differences. The current study utilized a scaling component (i.e., Hurst exponents) to classify students' interactions with game-based features as random or deterministic (i.e., controlled). Previous work has posited that an important aspect of self-regulation is a student's ability to control behaviors and act in a decisive manner [1, 7 – 8]. Thus, patterns that manifest within students' behaviors may reveal one component of self-regulated learning.

The analysis presented here is a potential means of covertly capturing one aspect of self-regulation (i.e., self-control). Students with higher Hurst exponents are said to be engaging in deterministic and controlled behavior patterns. Students with lower Hurst exponents are described as engaging in random behaviors. Random behaviors are associated with less purpose, control, or persistence. Results presented here indicate that these tendencies across time are related to students' daily learning outcomes. When students engaged in controlled behaviors, they were more likely to generate higher quality self-explanations across training. When this analysis was taken a step further, it was revealed that this relation held for the majority of training days when factoring out prior ability in self-explanation.

Although it is important to understand the impact that controlled interaction patterns have on daily learning outcomes, it is also important to identify students who are more inclined to engage in controlled patterns. Understanding how individual differences drive students' patterns of choices within adaptive environments has the potential to contribute to a deeper understanding of self-regulation. Thus, the current study investigated how individual differences in students' reading ability, prior expectations of computers, and commitment to learning was related to their propensity to interact with game-based features in a deterministic manner. The current findings indicated that only students' commitment to learning was positively related to controlled patterns of interactions within iSTART-ME. Hence, when students expressed a desire to learn, they were also likely to act in a decisive, persistent, controlled, and deterministic manner in the system. Self-regulation researchers have postulated that when students are motivated to achieve learning goals they are more likely to regulate their behaviors [30]. These findings support previous research, which reveals that self-regulation is related to students' learning goals [29]. Thus, students' ability to control their behaviors is not necessarily tied to their literacy skills or familiarity with computers. Indeed, students must choose to take an active role in their learning and behave in a manner that supports their learning goals. These findings are preliminary. Clearly, future research will call for better measures of learning orientation to gain a deeper understanding of how students' attitudes influence the nuanced ways in which they approach learning tasks within game-based environments. Nonetheless, these results contribute to theoretical notions of self-regulation by revealing potential relations between students' attitudes and patterns of controlled behaviors.

In sum, these exploratory findings are promising for educational researchers as they reveal how students' behavior patterns influence learning outcomes. The current work also begins to shed light upon the nuanced ways in which scientists may be able to trace and classify students' interactions within adaptive systems. These analyses provide evidence suggesting that dynamical methodologies may afford researchers an online stealth assessment of self-regulation. Future work calls for confirmatory studies focused on demonstrating concurrent validity as well as how these dynamical methods of analysis can be utilized to improve student models within adaptive systems. Namely, real time analysis may offer a useful means of measuring self-regulated behavior patterns without relying on self-report questionnaires. If student models are able recognize optimal vs. non-optimal patterns of interaction for each student, we expect that learning systems will more effectively adapt to students' needs based on students' behavior patterns.

5. REFERENCES

[1] McCombs, B. L. 1989. Self-regulated learning and academic achievement: A phenomenological view. In B. J. Zimmerman & D. H. Schunk (Eds.), *Self-regulated learning and academic achievement: Theory, research, and practice* (pp. 51-82). Springer New York: Springer-Verlag.

[2] Pintrich, P. R., and De Groot, E. V. 1990. Motivational and self-regulated learning components of classroom academic performance. *Journal of Educational Psychology, 82*, (1990) 33-40.

[3] Winne, P. H., and Nesbit, J. C. 1995. Graph theoretic techniques for examining patterns and strategies in learners' studying: An application of LogMill. Paper presented at the Annual Meeting of the American Educational Research Association, San Francisco, CA (April, 1995).

[4] Winne, P., and Hadwin, A. 1998. Studying as self-regulated learning. In Hacker, D., Dunlosky, J., and Graesser, A. (Eds.), *Metacognition in Educational Theory and Practice,* (pp. 279-306). Hillsdale, NJ: Erlbaum.

[5] Zimmerman, B. J. 1990. Self-regulated learning and academic achievement: An overview. *Educational psychologist, 25*, (1990), 3-17.

[6] Zimmerman, B. J., and Schunk, D. H. 1989. *Self-regulated learning and academic achievement: Theory, research, and practice*. New York: Springer-Verlag Publishing.

[7] Schunk, D. H. 2008. Metacognition, self-regulation, and self-regulated learning: Research recommendations. *Educational psychology review, 20* (2008), 463-467.

[8] Schunk, D. H., and Zimmerman, B. J. 2003. *Self‐regulation and learning. Handbook of psychology.*

[9] Hadwin, A. F., Nesbit, J. C., Jamieson-Noel, D., Code, J., and Winne, P. H. 2007. Examining trace data to explore self-regulated learning. *Metacognition and Learning, 2*, (2007), 107-124.

[10] Sabourin, J., Rowe, J., Mott, B., and Lester, J. 2011. When off-task is on-task: the affective role of off-task behavior in narrative-centered learning environments. *Proceedings of Artificial Intelligence in Education* (Auckland, New Zealand June 28 –July 1, 2011). Springer Berlin/Heidelberg, 534-536.

[11] Ellis, D., and Zimmerman, B. 2001. Enhancing self-monitoring during self-regulated learning of speech. In H. Hartman (Ed.), *Metacognition in Learning and Instruction* (Vol. 19). Kluwer, Dordrecht, The Netherlands, 205-228.

[12] Riding, R., and Rayner, S. 1998*. Cognitive styles and learning strategies: Understanding style differences in learning and behavior*. David Fulton Publishers, London.

[13] Satterly, D. J., and Brimer, M. A. 1971. Cognitive styles and school learning. *British Journal of Educational Psychology*, *41*, (1971) 294-303.

[14] Witkin, H. A., Moore, C. A., Goodenough, D. R., and Cox, P. W. 1977. Field-dependent and field-independent cognitive styles and their educational implications. *Review of educational research, 47*, (1977)1-64.

[15] Snow, E. L., Jackson, G. T., Varner, L. K., and McNamara, D. S. 2013. Expectations of technology: A factor to consider in game-based learning environments. In K. Yacef et al. (Eds.), *Proceedings of the 16th International Conference on Artificial Intelligence in Education* (Memphis, Tennessee, July 9 -12, 2013), Heidelberg, Berlin: Springer. 359-368.

[16] Snow, E. L., Likens, A., Jackson, G. T., and McNamara, D. S. 2013. Students' walk through tutoring: Using a random walk analysis to profile students. In S. K. D'Mello, R. A. Calvo, and A. Olney (Eds*.), Proceedings of the 6th International Conference on Educational Data Mining,* (Memphis, Tennessee, July 6 -9, 2013), Springer Berlin Heidelberg, 276-279.

[17] Jackson, G. T., Varner, L. K., Boonthum-Denecke, C., & McNamara, D. S. in press. The impact of individual differences on learning with an educational game and a traditional ITS. *International Journal of Learning Technology*.

[18] Jackson, G. T., and McNamara, D. S. 2013. Motivation and Performance in a game-based intelligent tutoring system. *Journal of Educational Psychology, 105*, (2013), 1036-1049.

[19] McNamara, D. S., O'Reilly, T., Rowe, M., Boonthum, C., and Levinstein, I. B. 2007. iSTART: A web-based tutor that teaches self-explanation and metacognitive reading strategies. *In Reading comprehension strategies: Theories, interventions, and technologies,* D. S. McNamara, Ed. Erlbaum. Mahwah, NJ, 397-420.

[20] Jackson, G. T., Boonthum, C., and McNamara, D. S. 2009. iSTART-ME: Situating extended learning within a game-based environment. *In Proceedings of the Workshop on Intelligent Educational Games at the 14th Annual Conference on Artificial Intelligence in Education*, (Brighton, UK, July 06 -10, 2009). AIED, IOS Press, 59-68.

[21] McNamara, D.S., Boonthum, C., Levinstein, I.B., and Millis, K. 2007. Evaluating self-explanations in iSTART: Comparing word-based and LSA algorithms. *In Handbook of Latent Semantic Analysis,* T. Landauer, D. S. McNamara, S. Dennis, and W. Kintsch, Eds. Erlbaum. Mahwah, NJ, 227-241.

[22] Jackson, G. T., Dempsey K. B., and McNamara, D. S. 2010. The evolution of an automated reading strategy tutor: From classroom to a game-enhanced automated system. In M.S. Khine & I.M. Saleh (Eds.), *New Science of learning: Cognition, computers and collaboration in education* (pp. 283-306). New York, NY:Springer.

[23] MacGinitie, W., and MacGinitie, R. 1989.*Gates MacGinitie reading tests.* Riverside. Chicago, IL.

[24] Phillips, L. M., Norris, S. P., Osmond, W. C., and Maynard, A. M. 2002. Relative reading achievement: A longitudinal study of 187 children from first through sixth grades. *Journal of Educational Psychology, 94,* (2002) 3-13.

[25] Lobry, J. R. 1996. Asymmetric substitution patterns in the two DNA strands of bacteria. *Molecular Biological Evolution, 13*, (1996) 660–665.

[26] Hurst, H. E. 1951. Long-term storage capacity of reservoirs. *Transactions of the American Society of Civil Engineers., 116,* (1951) 770-808.

[27] Van Orden, G. C., Holden, J. G., and Turvey, M. T. 2003. Self-organization of cognitive performance. Journal of *Experimental Psychology: General, 132*, (2003) 331-350.

[28] D'Mello, S. K., Taylor, R., and Graesser, A. C. 2007. Monitoring affective trajectories during complex learning. In D. S. McNamara & J. G. Trafton (Eds.), *Proceedings of the 29th Annual Meeting of the Cognitive Science Society* (Nashville, Tennessee, August 1-4, 2007) Cognitive Science Society, 203-208.

[29] Pintrich, P. R. 2000. An achievement goal theory perspective on issues in motivation terminology, theory, and research. *Contemporary Educational Psychology,* 25, (2000), 92-104.

[30] Bandura, A. 1991. Social cognitive theory of self-regulation. *Organizational behavior and human decision processes, 50*, (1991), 248-287.