Computers in Human Behavior 41 (2014) 62–70

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com/locate/comphumbeh

Emergent behaviors in computer-based learning environments: Computational signals of catching up

Erica L. Snow *, G. Tanner Jackson, Danielle S. McNamara

Arizona State University, Learning Sciences Institute, Tempe, AZ, United States

A R T I C L E   I N F O

Article history:
Published on March, 2014

Keywords:
Intelligent tutoring systems
Individual differences
Self-regulated learning
Agency
Log data
Dynamic analyses

A B S T R A C T

Self-regulative behaviors are dynamic and evolve as a function of time and context. However, dynamical fluctuations in behaviors are often difficult to measure and therefore may not be fully captured by traditional measures alone. Utilizing system log data and two novel statistical methodologies, this study examined emergent patterns of controlled and regulated behaviors and assessed how variations in these patterns related to individual differences in prior literacy ability and target skill acquisition. Conditional probabilities and Entropy analyses were used to examine nuanced patterns manifested in students' interaction choices within a computer-based learning environment. Forty high school students interacted with the game-based intelligent tutoring system iSTART-ME, for a total of 11 sessions (pretest, 8 training sessions, posttest, and a delayed retention test). Results revealed that high and low reading ability students differed in their patterns of interactions and the amount of control they exhibited within the game-based system. However, these differences converged overtime along with differences in students' performance within iSTART-ME. The findings from this study indicate that individual differences in students' prior reading ability relate to the emergence of controlled and regulated behaviors during learning tasks.

© 2014 Elsevier Ltd. All rights reserved.

1. Introduction

Intelligent Tutoring Systems (ITSs) are sophisticated computer-based learning environments (Graesser, McNamara, & VanLehn, 2005) that often incorporate multiple methods and trajectories for interaction based on each user's unique needs and abilities (Jackson & McNamara, 2013; Murray, 1999; Sabourin, Shores, Mott, & Lester, 2012; Snow, Jackson, & McNamara, 2014; Snow, Likens, Jackson, & McNamara, 2013). Consequentially, students often have different experiences and exhibit various levels of control during their time within these environments. Such varying experiences are often influenced by various individual differences (Baker, Corbett, Koedinger, & Wagner, 2004; Baker, Walonoski, Heffernan, Roll, Corbett, et al., 2008; Snow, Likens, et al., 2013); thus, ITSs provide researchers with a unique opportunity to examine how individual differences influence the way in which students choose to control their learning experience (Sabourin et al., 2012; Snow, Jacovina, Allen, Dai, & McNamara, 2014; Snow, Allen, Russell, & McNamara, 2014).

When students exert control over their behaviors during learning tasks it is often referred to self-regulated learning (SRL). This skill has been shown to be an important component of the learning process as it has led to positive effects on students' overall learning gains (Butler & Winne, 1995; Harris, Friedlander, Saddler, Frizzelle, & Graham, 2005; Järvelä & Järvenoja, 2011; Pintrich & De Groot, 1990; Zimmerman, 1990; Zimmerman, 2008; Zimmerman & Schunk, 1989, 2001, 2013). Zimmerman (1990) proposed that when students take personal responsibility over their scholarship, they are more likely to succeed than those students who do not. Self-regulated students frequently set goals, plan, organize, self-monitor, and self-assess during learning tasks, which allows them to remain actively aware of their own actions, knowledge, and decisions.

One characteristic of self-regulating students is their propensity to approach learning tasks in a decisive and goal directed manner (Zimmerman, 1990, 2008). Recently, researchers have investigated this characteristic within the context of ITSs (Hadwin, Nesbit, Jamieson-Noel, Code, & Winne, 2007; Sabourin et al., 2012; Snow, Jacovina, et al., 2014; Winters, Greene, & Costich, 2008). This work has shown that when students plan and exert control over their behaviors within a computer-based learning environment they perform better compared to those who do not (Hadwin et al., 2007; Sabourin et al., 2012; Snow, Jacovina, et al., 2014;

* Corresponding author at: Department of Psychology, Arizona State University, Tempe, AZ, United States. Tel.: +1 317 224 3188.
E-mail address: Erica.L.Snow@asu.edu (E.L. Snow).

http://dx.doi.org/10.1016/j.chb.2014.09.011
0747-5632/© 2014 Elsevier Ltd. All rights reserved.

Snow, Allen, Jackson, et al., 2014; Snow, Allen, Russell, et al., 2014). For instance, Sabourin et al. (2012) examined how students' behaviors within the immersive game-based environment, Crystal Island, related to their use of SRL strategies (e.g., self-monitoring and goal setting). Results revealed that students' with higher levels of SRL strategy use were also students who interacted within the game-based system in a goal oriented and planned fashion. Similarly, Snow et al. (2014) examined how students exhibited random or deterministic patterns of choice while they engaged within the game-based ITS, iSTART-ME. This work showed that when students engaged in random interaction patterns within the system interface, they performed worse than students who demonstrated controlled interaction patterns. Finally, Hadwin et al. (2007) utilized the web-based study software gStudy to examine how patterns in students' study habits related to self-report measures of SRL. This work revealed that ordered and goal driven study patterns were positively related to SRL abilities. Combined, these studies have found that students' ability to act in a controlled and goal directed way is a characteristic of SRL behavior.

Although self-regulation is crucial for academic success, this skill tends to vary widely, as many students struggle to set their own learning goals and actively monitor goals during learning tasks (Ellis & Zimmerman, 2001). One factor that has been linked to variations in students' ability to self-regulate is prior skill level (Kitsantas, Winsler, & Huie, 2008; McClelland et al., 2007; Zimmerman, Bandura, & Martinez-Pons, 1992). McClelland et al. (2007), for example, examined the relation between regulatory behaviors and emergent skills within preschoolers. They found that self-regulative behaviors were highly related to the students' scores on an academic aptitude test. Similarly, Zimmerman and Martinez-Pons (1986) found that students' scores on academic achievement tests were related to their SRL ability. Thus, higher skill levels seem to be related to SRL behaviors.

However, SRL ability is not static (i.e., unchanging), instead researchers have shown this ability is dynamic (Boekaerts, Pintrich, & Zeidner, 2000; Hadwin et al., 2007; Zhou, 2013) and evolves overtime (Glaser & Brunstein, 2007; Zimmerman, 2008). Such work has revealed that self-regulation is not simply something students either excel or fail at. Indeed there are many factors that can influence the evolution of this skill. For instance, Muraven, Baumeister, and Tice (1999) found that metacognitive strategy training is effective over time at improving students' self-regulatory behaviors. Similarly, Glaser and Brunstein (2007) showed that metacognitive strategy training improved students' SRL abilities. Thus, students who struggle to regulate their behaviors are able to improve this skill with the adequate instruction.

Although training has been shown to have positive effects on students' SRL ability, this skill can evolve naturally as well. Eshel and Kohavi (2003) demonstrated that students' ability to use SRL strategies improved when they were given high amounts of agency over their learning environment. Similarly, Bandura's (1991) Social Cognitive Theory links the process of self-regulation to personally agency. Bandura postulated that students who self-regulate exhibit reflective and reactive decision-making in their choices. Thus, improvements in SRL ability are not just accomplished through external factors such as training. Instead, students must take agency over their actions by deciding how to control and regulate their behaviors. Such choices are often reactionary and therefore evolve overtime as students gain more experience and receive increased amounts of feedback from a given environment (Bandura, 1991). This work has led to the hypothesis that when students are afforded opportunities to exert agency over their environment or a given situation, they may naturally begin to regulate their behaviors without external training or prompting.

This complex interplay between SRL and personal agency is especially relevant within the domain of ITSs. As discussed earlier, these computer-based learning environments often incorporate high levels of agency while presenting students with adaptive content as a means to engage and challenge them. Thus, the best indication of the evolution of students' regulatory skills is potentially through the examination of their ability to control and regulate their behaviors when they are presented with numerous options or trajectories. However the evolution of these behavioral changes, as can be expected, is difficult to measure and often overlooked through the use of traditional self-report measures. Static measures of SRL such as self-reports usually focus on students' memories for past behaviors; however, students may not be conscious of their changing behaviors. This renders the nuanced and dynamical patterns of behavior change hard to measure through self-report assessments alone.

One way to measure the evolution of students' self-regulated behaviors within adaptive environments is through the analysis of system log data (Hadwin et al., 2007). Log data (e.g., keystroke, mouse click, click stream, or telemetry data) records all student interactions within an adaptive environment. Researchers often intentionally program computer-based environments to capture this information as a means to examine fine-grained interactions within the interface. This type of data collection and analysis, although tedious, provides researchers with a wealth of information regarding how students choose to exert agency and control their behaviors within a system. Log data has been previously used to examine how students' interactions within ITSs influence their attitudes (Hadwin et al., 2007; Rai & Beck, 2012; Snow, Jackson, Varner, & McNamara, 2013a) and performance (Rowe, McQuiggan, Robison, & Lester, 2009; Snow, Jackson, Varner, & McNamara, 2013b). While informative, these prior studies have primarily focused on variations in students' interaction patterns at a coarse grain-size (e.g., frequency of interactions). To investigate how students exert agency while interacting within an adaptive system, more dynamic and fine-grained analyses that focus on the presence of nuanced patterns in students' behaviors are needed. The work presented here combines two dynamic methodologies (i.e., probability and Entropy analyses) to examine how individual differences in prior reading ability influence the evolution of students' choice patterns as they manifest over time and their subsequent relation to learning outcomes.

1.1. iSTART-ME

iSTART (Interactive Strategy Training for Active Reading and Thinking) is an intelligent tutoring system designed to provide self-explanation and comprehension strategy training to high school students (Jackson & McNamara, 2013; McNamara, Boonthum, Levinstein, & Millis, 2007). iSTART strategy instruction has been shown to be effective at improving students' comprehension and self-explanation ability (Jackson & McNamara, 2013; McNamara et al., 2007; O'Reilly, Sinclair, & McNamara, 2004; Taylor, O'Reilly, Rowe, & McNamara, 2006). iSTART consists of three modules: introduction, demonstration, and practice. Within the introduction module, students are provided a brief description self-explanation reading strategies. After the introduction module, students are transitioned into the demonstration module where two pedagogical agents (one teacher and one student) demonstrate how to apply the self-explanation strategies to example science texts. Finally, after students complete the demonstration module they are transitioned into the practice environment where they self-explain various target sentences from an example science text. The practice module is designed to provide students with the opportunity to apply the information that they learned within the introduction and demonstration modules.iSTART-ME (Motivationally Enhanced) is a game-based version of iSTART that provides students with strategy training within the context of an interactive game-based environment (Jackson, Boonthum, & McNamara, 2009; Jackson, Dempsey, & McNamara, 2010; Jackson & McNamara, 2013). iSTART-ME is similar to iSTART with the exception that after the practice module students are transitioned into an extended practice menu that uses game-based principles and features to enhance students' motivation, engagement, persistence, and learning throughout long-term practice (Cordova & Lepper, 1996; McNamara, Jackson, & Graesser, 2010; Ricci, Salas, & Cannon-Bowers, 1996). Students control their iSTART-ME extended practice experience through a game-based selection menu (see Fig. 1). This menu was designed to enhance students' feelings of agency over the environment by affording the opportunity to choose what to do.

Within the iSTART-ME extended practice selection menu, students can choose to interact with four types of game-based features (i.e., generative practice games, identification mini-games, personalizable features, and achievement screens). Generative practice games are designed to provide students with the opportunity to practice generating their own self-explanations within the context of a game narrative. In these games, students are shown a text and then are asked to generate a self-explanation of the text that they had just seen. Students' generated self-explanations are assessed by the iSTART algorithm, which combines latent semantic analysis (LSA; Landauer, McNamara, Dennis, & Kintsch, 2007) and word-based measures. This algorithm yields scores on a range of 0–3. Self-explanations are assigned a score of "0" when they are composed of irrelevant information. A score of "1" is assigned when students' self-explanations relate to the target sentence but do not elaborate upon any of the given information. A score of "2" is assigned to self-explanations that incorporate information outside of the target sentence. A score of "3" is assigned to self-explanations that incorporate information about the target sentence from their prior knowledge. This algorithm has been shown to score self-explanations comparable to expert human raters (Jackson, Guess, & McNamara, 2009; McNamara et al., 2007).

Identification mini-games are designed to provide students with a different type of strategy instruction, mainly, strategy recognition practice. In identification mini-games, students are shown a text and a corresponding self-explanation; they are prompted to select which of the previously learned strategies was used to generate the example self-explanation. The extended practice game-based menu also allows students to monitor their performance within the system by accessing achievement screens. These pop-up screens allow students to view how they have performed in both the identification mini-games and within the generative practice games. Finally, students can also choose to personalize the system interface by changing the background color or editing an avatar. These four types of game-based features (generative practice, identification mini-games, achievement screens, and personalizable features) provide students with a substantial amount of control and personalization over their experience within iSTART-ME.

1.2. Current study

iSTART-ME has been effective at sufficiently motivating students while maintaining effective self-explanation instruction (Jackson, Davis, Graesser, & McNamara, 2011; Jackson & McNamara, 2013). However, this system provides students with an opportunity to exert high amounts of agency over their learning experience. Thus, iSTART-ME affords researchers a unique opportunity to examine how students control and regulate their experiences by investigating *how* they choose to interact with various system features and *what* factors are mitigating these interactions. Previous work has shown that students' ability levels are highly related to their ability to self-regulate (Kitsantas et al., 2008; McClelland et al., 2007; Zimmerman et al., 1992). This study builds off of this work while also taking advantage of the unique design of the iSTART-ME interface to examine how individual differences in reading ability influence students' behaviors (i.e., patterns of interactions) and subsequent learning outcomes. The ultimate goal of iSTART-ME is to improve reading comprehension ability; thus, understanding how the effects of this intervention depend on prior ability is crucial in evaluating the effectiveness of the system. To this end, this study investigates the extent to which prior reading ability is a mitigating factor in students' ability to control their behaviors during a learning task. In this study there are four primary questions.

(1) Do differences in target skill performance between high and low reading ability students emerge over time?
(2) Do dynamic analyses successfully capture variations in students' choice patterns with game-based features as they manifest across multiple training sessions?
(3) How do students' interaction patterns vary as a function of individual differences in prior reading ability level?
(4) Do variations in students' choice patterns associated with reading ability emerge over time?

Fig. 1. Screenshot of iSTART-ME selection menu.

A unique contribution of this study stems from the dynamic analysis of log data to investigate which game-based features students interact with and how. Our goal is to provide researchers with deeper understanding of how students' ability to exert control and regulate themselves emerges and manifest across time.

2. Method

2.1. Participants

This study included 40 high-school students (50% male; mean grade level of 10.4; mean age of 15.5 years; 17% were Caucasian, 73% were African-American, and 10% reported other nationalities), from a mid-south urban environment. The sample included in this study is a subset of 124 students who participated in a larger efficacy study that compared learning gains across three conditions: iSTART-ME, iSTART-Regular, and a no-tutoring control (for more information see Jackson & McNamara, 2013). The current work focuses solely on the students who were assigned to the iSTART-ME condition, as they were the ones who had access to the full game-based system.

2.2. Procedure

Students completed an 11 session experiment consisting of a pretest, eight training sessions, a posttest, and a delayed retention test. During the first session, students answered a battery of questions. Particularly relevant for the current work, this pretest included an assessment of prior self-explanation (SE) ability and a standard measure of reading comprehension (Gates-MacGinitie Reading Test; MacGinitie & MacGinitie, 1989). During the subsequent eight sessions, participants interacted with the iSTART-ME system, which included the introduction, demonstration, practice and extended practice modules. Each training session lasted approximately 1 h; during this time students were free to interact with any feature in the extended practice interface, which included generative practice, identification mini-games, personalizable features, and achievement screens. The data reported in this study primarily focus on students' interactions with these game-based features during extended practice. These eight training session were originally designed to compare the effects of games versus non-games over long-periods of time (Jackson & McNamara, 2013); however, the current work utilizes the log data from iSTART-ME to begin to understand how students control and regulate their behaviors during learning tasks. During the 10th session, students completed a posttest, which was included a measure of self-explanation ability similar to the one in the pretest. One week after the posttest, students completed a retention test with measures assessing long-term self-explanation ability.

2.3. Materials and measures

2.3.1. Reading comprehension

Students' reading comprehension was assessed using the Gates-MacGinitie Reading Test (MacGinitie & MacGinitie, 1989). This test included 48 questions designed to assess the general reading ability of each student. In this task students were asked to read a passage of text and then answer two to six comprehension questions about the material in the passage. Students were given 20 min to complete the test. This test is a well-established measure that provides information about students' reading comprehension ability (α = .85–.92, Phillips, Norris, Osmond, & Maynard, 2002).

2.3.2. Self-explanation ability

During the pretest, posttest, and retention students completed a self-explanation task, which was scored on a scale of 0–3, using the previously described iSTART algorithm scoring system. Students read through one of three science texts and provided self-explanations for specified target sentences (for a total of eight self-explanations per text). Self-explanation scores were averaged to provide a measure of students' ability at each testing time. Students' self-explanations were also evaluated during the training portion of the study and scored using the iSTART algorithm.

2.3.3. Interaction categories

Students' interactions in iSTART-ME were logged within the iSTART-ME database. This process data was then organized according to the function afforded by each feature: generative practice, identification mini-games, personalizable features, and achievements screens.

2.3.3.1. Generative practice. Within iSTART-ME, students have the opportunity to engage in practice that requires them to generate their own self-explanations for a presented text (center box in Fig. 1). An activity was categorized as generative practice when students chose to engage with any of the three practice environments: Coached Practice, Map Conquest, and Showdown.

2.3.3.2. Identification mini-games. In addition to generative practice, six mini-games provide a different form of practice that targets the iSTART-ME strategies (bottom-right column of Fig. 1). As described earlier, these games present a text with an example self-explanation, requiring students to identify which strategies were used within the example provided.

2.3.3.3. Personalizable features. Within iSTART-ME, students have the opportunity to personalize features within their environment, including editing an avatar, customizing the background theme, or changing their pedagogical agent (bottom-left options in Fig. 1).

2.3.3.4. Achievement screens. As students progress through the iSTART-ME system they have the opportunity to earn points, win trophies, and advance to higher skill levels. These options are available throughout the system as mouse-overs or pop-up screens. For example, students can click on "My Trophies" (right-side of Fig. 1) to view a record of their trophy achievements across all practice environments within iSTART-ME.

3. Quantatative methods

The iSTART-ME system captures and records all interactions that students perform within the extended practice selection menu. This study utilizes time-stamped process data to chronologically categorize each student's choices across the multiple training sessions. Overall, there were 11,343 interactions logged with each student making an average of 284 interactions across all 8 training sessions. Leveraging this extensive dataset, the probability of each student's set of interactions and the amount of order (i.e., Entropy) that they exerted while engaging with these game-based features was calculated. These methodologies are of particular importance to understanding the emergence of patterns within students' choices as they both capture dynamic movements (or changes) that are often missed by more traditional (i.e., static) measures. This study is one of the first to use of both probability and Entropy analyses to capture nuanced patterns that emerge within students' choice patterns.

3.1. Conditional probabilities

Students' probabilities of interactions were calculated using a statistical sequencing procedure similar to that used in D'Mello, Taylor, and Graesser (2007). This calculation can be described as $L[I_t \rightarrow X_{t+1}]$, where L is the likelihood function of the student's current interaction (I) at specific time point t, and X is the next interaction at the next time point ($t + 1$). More simply, we calculated the probability of a student's interaction with an interface feature given their previous interaction. For instance, if Jane interacts with a generative practice game, we will use the above formula to examine what feature Jane is most likely to interact with next (e.g., another generative practice, an identification mini-game, a personalizable feature, or an achievement screen). These likelihood probabilities were calculated for each interaction transition yielding a unique pattern for each student.

3.2. Entropy

Students' propensity to engage with game-based features within iSTART-ME in an ordered fashion was calculated using Shannon Entropy (Shannon, 1951). Entropy is a statistical measure derived from thermodynamics that classifies the order of a time series (Clausius, 1865). This measure classifies the probability of uncertainty (e.g. order) in a system (see Formula 1; pi is the probability of a given state). Entropy has previously been used in psychology to investigate patterns of order in students' choices (Fasolo, Hertwig, Huber, & Ludwig, 2009; Grossman, 1953; Snow, Jacovina, et al., 2014). For instance, Snow and colleagues used Entropy analysis to quantify how students' behaviors varied (i.e., were random or controlled) during game-play. These analyses provided a fine-grained metric of ordered behavior that would have otherwise been missed. Indeed, Entropy provides a deeper understanding of how students choose to regulate their interactions by examining the amount of order exhibited in their choice of interactions. In general, low Entropy suggests highly organized choice patterns, whereas high Entropy suggests disorganized choice patterns. Within the context of this study, Entropy scores of 0 would be indicative of perfect order. This means that a pattern consists of the exact same interaction over and over again. For instance, if Joe was to select an identification mini-game 10 times and he chooses nothing else, his Entropy score would be 0. Conversely, within the context of this study the highest Entropy score a student can earn is 2, which would be indicative of a disordered selection pattern. Thus, through the use of an Entropy analysis we can capture the amount of order (or disorder) present in students' choice pattern.

$$H(x) = -\sum_{i=0}^{N} P(x_i)(\log_e P(x_i)) \tag{1}$$

4. Results

This study examines how differences in students' ability to control their behaviors (i.e., interaction choices within iSTART-ME) relates to their target skill acquisition (i.e., daily self-explanation quality) and varies as a function of prior reading ability. First, using repeated measures analysis of variance, we examine differences in learning outcomes between high and low reading ability students. Conditional probability and Entropy analyses are then calculated on students' log data to investigate *how* they interacted within the iSTART-ME system. Finally, we investigate how high and low reading ability students vary in their use (i.e., probability of interaction) and control (i.e., Entropy) of various game-based features embedded within iSTART-ME.

4.1. Learning outcomes

Prior research has examined how students, of varying abilities, performed differently during interactions within the iSTART system (Jackson, Boonthum, & McNamara, 2010; Jackson, Boonthum-Denecke, & McNamara, 2012; Jackson, Varner, Boonthum-Denecke, & McNamara, 2013). Specifically, results from these studies have revealed that students with low prior reading ability improve performance across time, catch up, and become indistinguishable from high reading ability students in terms of performance. Hence, one goal of this study is to examine how individual differences in reading ability are related to changes in students' self-explanation quality across time. A repeated-measures ANOVA revealed a significant main effect for testing time, indicating that students significantly improved their self-explanation quality scores from pretest ($M = 1.52$, $SD = .62$) to posttest ($M = 2.11$, $SD = .63$), $F(1,38) = 26.05$, $p < .001$. To investigate the impact of individual differences on self-explanation quality, a median split was conducted on students' pretest reading comprehension scores (creating high and low ability groups of students). An ANOVA using the median split on reading comprehension indicated that low ability students ($M = 1.35$, $SD = .61$) generated significantly lower quality self-explanations at pretest than high ability students ($M = 1.78$, $SD = .55$), $F(1,38) = 5.13$, $p < .05$. In contrast, an ANOVA on the posttest scores revealed that the self-explanation quality of students with a low prior reading ability ($M = 2.11$, $SD = .68$) was not significantly different from high ability students ($M = 2.12$, $SD = .57$; $F(1,38) = 0.01$, $p = .96$). A mixed factor repeated-measures ANOVA, including the median split with the pretest and posttest self-explanation scores, yielded a marginally significant interaction between testing time and students' reading ability, $F(1,38) = 3.73$, $p = .06$. These results reveal that both high and low ability students improved their self-explanation skills from pretest to posttest and interestingly, by the end of the 8 training sessions, low ability students were able to match the posttest outcomes of high ability students.

To examine how the differences in self-explanation quality emerge over time, analyses were performed to examine students' self-explanation quality scores during training (see Fig. 2). A mixed-factors ANOVA on students' self-explanation scores during training indicated a significant linear interaction between reading ability and training session, $F(1,29) = 5.43$, $p < .05$. Thus, students with low prior reading ability tended to improve self-explanation scores across sessions and over time performed more similarly to students with high reading ability. Bonferroni-adjusted pairwise comparisons indicated that high ability students produced significantly better self-explanation scores than low ability students for Days 1 ($t = 5.89$, $p^{adjusted} < .01$), 2 ($t = 3.96$, $p^{adjusted} < .01$), 3 ($t = 3.89$, $p^{adjusted} < .01$), 4 ($t = 2.27$, $p^{adjusted} < .05$), 5 ($t = 2.87$, $p^{adjusted} < .01$), and 7 ($t = 2.74$, $p^{adjusted} < .05$). In contrast, adjusted pairwise comparisons indicated that low and high ability students did not produce significantly different self-explanation scores dur-

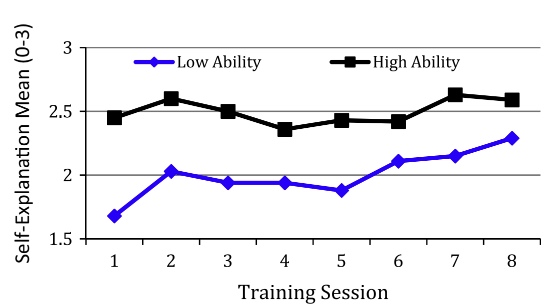

Fig. 2. Self-explanation performance during training.

ing Days 6 ($t = 1.65$, $p^{adjusted} > .05$) and 8 ($t = 1.82$, $p^{adjusted} > .05$). This trend suggests that students with low prior reading ability are able to improve their self-explanation quality, and by the end of training perform similar to the high reading ability students.

4.2. Overall transitional probability patterns

One explanation for why the learning trends observed in this study may emerge relates to the assumption that the low ability students' control and regulatory behaviors evolve while they engage within iSTART-ME. Indeed, previous work has shown that students' ability to regulate and control their behaviors develops across time (Eshel & Kohavi, 2003). Thus, a question inherent to this study regards the patterns of interactions within iSTART-ME and how those differ as a function of students' prior ability. To investigate how individual differences in students' pretest reading comprehension ability impacted the way in which students behaved and interacted within the game-based system, a transitional probability analysis was conducted (Fig. 3). This analysis revealed significantly different patterns between the two ability groups. Fig. 3 provides a visual display of the transition probabilities for each group (high ability in black and low ability in purple), with numbers inside a box representing the likelihood of selecting the same feature again, and numbers near a line indicating the likelihood of transitioning from one feature to another. Overall, students spent the majority of their time interacting with and transitioning between generative practice games and identification mini-games (high ability 76%; low ability 72%). By examining the trends for each ability level, patterns indicate that low ability students were significantly more likely to interact with the generative practice games, $F(1,38) = 6.23$, $p < .05$, whereas high ability students were more likely to interact with the identification mini-games $F(1,38) = 16.62$, $p < .001$ (see asterisks in Fig. 3 for significantly different patterns). Low ability students were also more likely to check their personal achievement screens before, $F(1,38) = 6.39$, $p < .05$, and after $F(1,38) = 6.09$, $p < .05$, they interacted with a generative practice game. Thus, low ability students seem to be monitoring their progress through the system (via achievement screens). These patterns indicate that students' abilities affect how they interact with the computer-based learning environment in a variety of ways.

4.3. Interactions choices across time

The overall transitional probability analyses provide some insight into how students' patterns of interactions within a

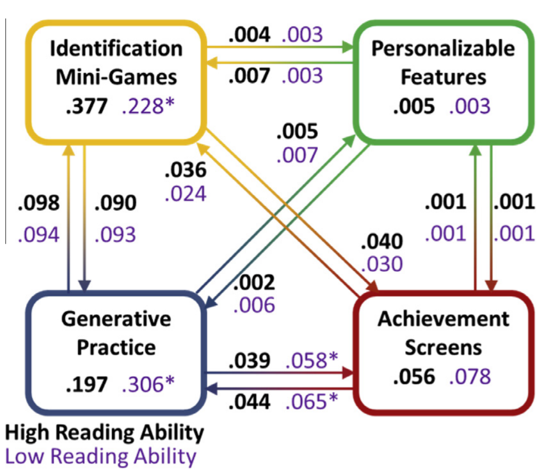

Fig. 3. Transition probabilities for high and low reading ability students. $p < .05^*$

game-based ITS varied as a function of individual differences in reading ability. However, the previous analyses provide little information about how these differences manifest overtime. Using the median split on Gates reading comprehension, interaction probabilities were calculated separately across all training sessions (see Fig. 4). Most students spent the first session going through the introduction, demonstration, and part of regular coached practice (i.e., they did not progress into the selection menu on training sessions one). However, the majority students began to interact with the selection menu during the second session. Thus, Fig. 4 displays the distribution differences between the low and high ability readers for session 2–8. During the first session with the selection menu (Day 2 in Fig. 4), all students use the system features in similar patterns (i.e., there are no significant differences in the probability distribution). However, high ability students chose to interact with the identification mini-games significantly more often than did the low ability students on Days 3 ($F(1,38) = 10.86$, $p < .001$), 4 ($F(1,38) = 12.35$, $p < .001$), and 5 ($F(1,38) = 15.02$, $p < .001$). Conversely, the low ability students chose to engage with generative practice significantly more often than the high ability students on Days 3 ($F(1,38) = 5.73$, $p < .05$), 4 ($F(1,38) = 13.58$, $p < .001$), and 5 ($F(1,38) = 13.52$, $p < .001$). Interestingly, the identification mini-game probability transitions between low and high ability students converge across training and are no longer significantly different by training Days 6 ($F(1,38) = 3.78$, $p = .06$), 7 ($F(1,37) = 1.19$, $p = .20$), and 8 ($F(1,29) = 1.41$, $p = .24$). Similarly, the differences between high and low ability students in probability of interactions with generative practice games converge on Day 6 ($F(1,38) = 2.20$, $p = .15$), 7 ($F(1,37) = 1.17$, $p = .20$), and 8 ($F(1,28) = .69$, $p = .41$).

The results illustrated in Fig. 4 indicate that high ability students quickly settle into a pattern that is consistent across Days (3–8) and predominantly focus on the identification mini-games (roughly 40–50% of all choices). By contrast, the low ability students initially focus on the generative practice (which provides them with more scaffolding and feedback), and later transition into a pattern almost identical to high ability users. These results suggest that low ability students are regulating their learning (as also suggested in Fig. 3) and adapting their system choices based on the level of their performance.

4.4. Measure of order in interaction patterns across time

To investigate how students of varying reading ability regulated and controlled their behaviors across multiple sessions, an Entropy analysis was conducted. Using the median split on Gates reading comprehension, Entropy was calculated separately for each student across training Days 2–8 (see Fig. 5). During the first session with the selection menu (Day 2 in Fig. 5), low ability students' interactions patterns demonstrated higher levels of Entropy compared to high ability students $F(1,38) = 4.507$, $p < .05$. Thus, low ability students demonstrated a more disorganized interaction pattern compared to high ability students during the first session within the interface. During Days 3–6, this variation in order disappears as students of both high and low ability show comparable levels of Entropy (i.e., order) within their choice patterns. Interestingly, on Day 7, low ability students again show significantly more disorder with their choice patterns compared to high ability students, $F(1,38) = 4.47$, $p < .05$. However, on Day 8 there are no differences in amount of demonstrated order between high and low ability students. Interestingly, the days when low ability students show more disorder in their choice patterns correspond to days when these students are interacting with a new feature predominantly for the first time. On Day 2, the system is novel to all students; thus they may not know what to expect or how to effectively make choices within the system. Similarly, Entropy dif-

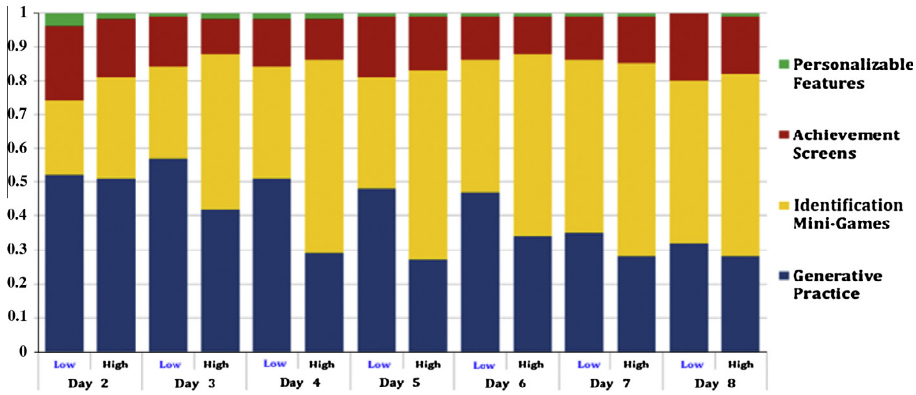

Fig. 4. Feature selections for high and low reading ability students.

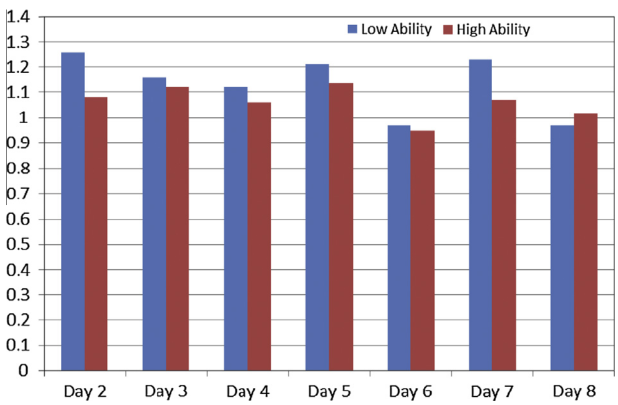

Fig. 5. Individual differences in Entropy across sessions.

ferences on Day 7 correspond to the first day when low ability students switch their choice patterns to mirror the high ability students (i.e., identification mini-games). These results suggest that when low ability students begin interacting more frequently with novel features, they demonstrate a more disorganized choice pattern compared to high ability students. However, this disorganization dissipates over time.

5. Discussion

ITSs often offer students a high level agency as a means to create a personalized learning experience. These experiences have been found to vary as a function of various individual differences (Baker et al., 2008; Snow et al., 2013b; Snow, Allen, Jackson, & McNamara, 2014). This study examines how students control and regulate their behaviors by investigating *how* they choose to interact with specific game-based features and *why* they chose to engage with them. Using two novel methodologies, conditional probability and Entropy analyses, we attempt to gain a deeper understanding of how various system trajectories form and manifest overtime. The current work revealed differences in behavior patterns (and performance) between students of low and high prior reading ability. These results provide computational signals of how students vary in their ability to regulate their behaviors across time, and potentially *catch up* to their more skilled peers.

Over the course of training within iSTART-ME, students with low prior reading ability were able to catch up and match the performance of high ability students (right-side of Fig. 2). This finding replicates previous work with the original version of iSTART, which found that over time, low ability students were able to improve performance and match the performance of high ability students (Jackson et al., 2010, 2013). To examine what could be contributing to the merging of these performance differences we investigated how students chose to regulate and control their behaviors while engaging with the iSTART-ME interface.

The overall transitional probability analyses revealed that high ability students choose to engage with the identification mini-games significantly more often than the low ability students (Fig. 3). In contrast, low ability students interact significantly more with the generative practice environments. Interestingly, the low ability students tend to monitor their system progress while interacting with generative practice games, as evidenced by a significantly higher rate of transitions to and from achievement screens. Thus, it appears that the low ability students are tracking their progress through the computer-based learning environment, and may also be adapting their behavior accordingly. This finding is contradictory to previous work that has found that high ability students are more likely to monitor and observe their behavior during learning tasks (Schunk, 1983, 2008). However, in this study students were engrossed in a game-based environment where they received varying levels of feedback based on the interactions they chose. Thus, as low ability students interacted more frequently with generative practice games (where they received a relatively steady dose of feedback), they may have been more aware of their performance within the system. Indeed, this relatively steady stream of feedback may have made the students more aware of their progress and inadvertently prompted them to monitor their achievements more frequently.

To examine emergent behavior patterns between high and low reading ability students a separate probability analyses across training sessions was also conducted. The distributions represented within Fig. 4 suggest that during the first few sessions, low ability students choose to interact most frequently with the generative practice environments. In contrast, students with a high reading ability tend to engage with the various identification mini-games (approximately half of the time). Examining the trends in Fig. 4, it is also evident that the low ability students adapt their interaction patterns across time (i.e., the distribution of choices changes from Day 3 through 7), and ultimately mirror the behaviors of high ability students.

The probability analyses demonstrated differences in which game-based features students chose to interact. While informative, these analyses alone cannot capture whether or not there is order present in those interaction patterns. Thus, using an Entropy analysis, we were able to distinguish differences in the way in which low and high ability demonstrated controlled patterns of interaction. The distributions represented within Fig. 5 suggest that during the first session, low ability students interacted in a more disordered fashion compared to students with a high reading ability. However, this difference disappears between Days 3 and 6, where both groups of students engage in an ordered fashion. Although high and low ability students interact with different features, both groups demonstrate controlled and ordered patterns of interactions. This is a characteristic of SRL and thus suggests that both high and low ability students regulate their behaviors, albeit in different ways. On Day 7, we observed, again, that low ability students revealed more disorder in their interaction patterns. Interestingly this resurgence of disorder coincides with the first day that low ability students began interacting with identification mini-games at a comparable rate to the high ability students. Subsequently, when low ability students changed their interactions they also generated significantly lower self-explanation quality scores compared to the high ability student. These results support the notion that with time and practice, low ability students can effectively self-regulate their interactions within learning environments, particularly when these environments are game-based.

These exploratory analyses begin to reveal computational signals of *catching up* that vary as a function of individual differences in reading ability and thus, impact corresponding learning outcomes. However, more research on individual differences and their impact on students' interactions with system features are still needed. Specifically, it is useful to understand how students' prior experience with technology or video games influences the ways in which they regulate and control their behaviors within ITSs. Expanding this type of work will allow researchers to improve the designs of learning environments that adapt to students' strengths and preferences. Specifically, future research should identify optimal and non-optimal behaviors; examine how to recognize these patterns in real-time, and design effective methods for adapting the system to match students' needs.

One limitation of this study is that no traditional self-report measure of SRL used. Traditionally, researchers have used self-reports to assess students' regulatory abilities. However, in the current work we relied upon log data analysis to capture behaviors as they occurred and evolved during the learning task. In the future, confirmatory studies demonstrating concurrent validity are needed to examine how the dynamic analysis of log-data relates to traditional measures of SRL behaviors.

The findings presented in this paper are some of the first to trace students' interaction patterns and subsequent learning gains across time at both coarse-grained and fine-grained levels. Consequently, these results reveal how students' interaction patterns manifested and emerged over time while also varying as a function of individual differences in reading ability. These new and innovative methods afford researchers the opportunity to assess variations in students' behaviors overtime and their ultimate impact on targeted skills. These results provide valuable insight into *how* users interact with complex environments through various behaviors, as well as *why* these different patterns emerge.

Acknowledgements

This research was supported in part by the Institute for Educational Sciences (IES R305G020018-02; R305G040046, R305A0 80589) and National Science Foundation (NSF REC0241144; IIS-0735682). Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the IES or NSF. A special thank you to Sidney D'Mello for his software assistance. We would also like to thank Laura Allen for her helpful comments on this manuscript, Chutima Boonthum for her help with programming, and all the other members of the Solet Lab for their assistance with data collection.

References

Baker, R. S., Corbett, A. T., Koedinger, K. R., & Wagner, A. Z. (2004). *Off-task behavior in the cognitive tutor classroom: When students "game the system". Proceedings of ACM CHI 2004: Computer–human interaction*. ACM: New York, pp. 383–390.

Baker, R., Walonoski, J., Heffernan, N., Roll, I., Corbett, A., & Koedinger, K. (2008). Why students engage in "gaming the system" behavior in interactive learning environments. *Journal of Interactive Learning Research, 19*, 185–224.

Bandura, A. (1991). Social cognitive theory of self-regulation. *Organizational Behavior and Human Decision Processes, 50*(2), 248–287.

Boekaerts, M., Pintrich, P. R., & Zeidner, M. (Eds.). (2000). *Handbook of self-regulation*. San Diego, CA: Academic Press.

Butler, D. L., & Winne, P. H. (1995). Feedback and self-regulated learning: A theoretical synthesis. *Review of Educational Research, 65*(3), 245–281.

Clausius, R. (1865). *The mechanical theory of heat—with its applications to the steam engine and to physical properties of bodies*. London, England: John van Voorst.

Cordova, D. I., & Lepper, M. R. (1996). Intrinsic motivation and the process of learning: Beneficial effects of contextualization, personalization, and choice. *Journal of Educational Psychology, 88*, 715–730.

D'Mello, S. K., Taylor, R., & 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* (pp. 203–208). Austin, TX: Cognitive Science Society.

Ellis, D., & Zimmerman, B. J. (2001). Enhancing self-monitoring during self-regulated learning of speech. In H. J. Hartman (Ed.), *Metacognition in learning and instruction. Theory, research, and practice* (pp. 205–228). Dordrecht: Kluwer Academic Press.

Eshel, Y., & Kohavi, R. (2003). Perceived classroom control, self-regulated learning strategies, and academic achievement. *Educational Psychology, 23*(3), 249–260.

Fasolo, B., Hertwig, R., Huber, M., & Ludwig, M. (2009). Size, entropy, and density: What is the difference that makes the difference between small and large real-world assortments? *Psychology and Marketing, 26*(3), 254–279.

Glaser, C., & Brunstein, J. C. (2007). Improving fourth-grade students' composition skills: Effects of strategy instruction and self-regulation procedures. *Journal of Educational Psychology, 99*(2), 297–310.

Graesser, A. C., McNamara, D. S., & VanLehn, K. (2005). Scaffolding deep comprehension strategies through Point & Query, AutoTutor, and iSTART. *Educational Psychologist, 40*, 225–234.

Grossman, E. R. F. W. (1953). Entropy and choice time: The effect of frequency unbalance on choice-response. *Quarterly Journal of Experimental Psychology, 5*(2), 41–51.

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

Harris, K. R., Friedlander, B. D., Saddler, B., Frizzelle, R., & Graham, S. (2005). Self-monitoring of attention versus self-monitoring of academic performance: Effects among students with ADHD in the general education classroom. *Journal of Special Education, 39*, 145–156.

Jackson, G. T., Boonthum, C., & McNamara, D. S. (2010). The efficacy of iSTART extended practice: Low ability students catch up. In J. Kay & V. Aleven (Eds.), *Proceedings of the 10th international conference on intelligent tutoring systems* (pp. 349–351). Berlin/Heidelberg: Springer.

Jackson, G. T., Boonthum, C., & McNamara, D. S. (2009). ISTART-ME: Situating extended learning within a game-based environment. In H. C. Lane, A. Ogan, & V. Shute (Eds.), *Proceedings of the workshop on intelligent educational games at the 14th annual conference on artificial intelligence in education* (pp. 59–68). Brighton, UK: AIED.

Jackson, G. T., Boonthum-Denecke, C. B., & McNamara, D. S. (2012). A comparison of gains between educational games and a traditional ITS. In P. M. McCarthy & G. M. Youngblood (Eds.), *Proceedings of the 25th international Florida artificial intelligence research society (FLAIRS) conference* (pp. 444–449). Menlo Park, CA: The AAAI Press.

Jackson, G. T., Davis, N. L., Graesser, A. C., & McNamara, D. S. (2011). Students' enjoyment of a game-based tutoring system. In *Proceedings of the 15th international conference on artificial intelligence in education* (pp. 475–477). Auckland, New Zealand: AIED.

Jackson, G. T., Dempsey, K. B., & 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.

Jackson, G. T., Guess, R. H., & McNamara, D. S. (2009). Assessing cognitively complex strategy use in an untrained domain. *Topics in Cognitive Science, 2*, 127–137.

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

Jackson, G. T., Varner, L. K., Boonthum-Denecke, C., & McNamara, D. S. (2013). The impact of individual differences on learning with an educational game and a traditional ITS. *International Journal of Learning Technology, 8*, 315–336.

Järvelä, S., & Järvenoja, H. (2011). Socially constructed self-regulated learning and motivation regulation in collaborative learning groups. *Teachers College Record, 113*(2), 350–374.

Kitsantas, A., Winsler, A., & Huie, F. (2008). Self-regulation and ability predictors of academic success during college: A predictive validity study. *Journal of Advanced Academics, 20*(1), 42–68.

Landauer, T. K., McNamara, D. S., Dennis, S. E., & Kintsch, W. E. (2007). *Handbook of latent semantic analysis*. Lawrence Erlbaum Associates Publishers.

MacGinitie, W. H., & MacGinitie, R. K. (1989). *Gates MacGinitie reading tests*. Chicago: Riverside.

McClelland, M. M., Cameron, C. E., Connor, C. M., Farris, C. L., Jewkes, A. M., & Morrison, F. J. (2007). Links between behavioral regulation and preschoolers' literacy, vocabulary, and math skills. *Developmental Psychology, 43*(4), 947–959.

McNamara, D. S., Boonthum, C., Levinstein, I. B., & Millis, K. (2007). Evaluating self-explanations in iSTART: Comparing word-based and LSA algorithms. In T. Landauer, D. S. McNamara, S. Dennis, & W. Kintsch (Eds.), *Handbook of latent semantic analysis* (pp. 227–241). Mahwah, NJ: Erlbaum.

McNamara, D. S., Jackson, G. T., & Graesser, A. C. (2010). Intelligent tutoring and games (ITaG). In Y. K. Baek (Ed.), *Gaming for classroom-based learning: Digital role-playing as a motivator of study* (pp. 44–65). Hershey, PA: IGI Global.

Muraven, M., Baumeister, R. F., & Tice, D. M. (1999). Longitudinal improvement of self-regulation through practice: Building self-control strength through repeated exercise. *The Journal of Social Psychology, 139*(4), 446–457.

Murray, T. (1999). Authoring intelligent tutoring systems: An analysis of the state of the art. *International Journal of Artificial Intelligence in Education, 10*, 98–129.

O'Reilly, T. P., Sinclair, G. P., & McNamara, D. S. (2004). Reading strategy training: Automated versus live. In K. Forbus, D. Gentner, & T. Regier (Eds.), *Proceedings of the 26th annual cognitive science society* (pp. 1059–1064). Mahwah, NJ: Erlbaum.

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

Pintrich, P. R., & De Groot, E. V. (1990). Motivational and self-regulated learning components of classroom academic performance. *Journal of Educational Psychology, 82*(1), 33–40.

Rai, D., & Beck, J. (2012). Math learning environment with game-like elements: An experimental framework. *International Journal of Game Based Learning, 2*, 90–110.

Ricci, K., Salas, E., & Cannon-Bowers, J. A. (1996). Do computer-based games facilitate knowledge acquisition and retention? *Military Psychology, 8*, 295–307.

Rowe, J., McQuiggan, S., Robison, J., & Lester, J. (2009). Off-task behavior in narrative-centered learning environments. In *Proceedings of the fourteenth international conference on artificial intelligence and education* (pp. 99–106).

Sabourin, J., Shores, L. R., Mott, B. W., & Lester, J. C. (2012). Predicting student self-regulation strategies in game-based learning environments. In *Intelligent tutoring systems* (pp. 141–150). Berlin, Heidelberg: Springer.

Schunk, D. H. (1983). Ability versus effort attributional feedback: Differential effects on self-efficacy and achievement. *Journal of Educational Psychology, 75*, 848–856.

Schunk, D. H. (2008). Metacognition, self-regulation, and self-regulated learning: Research recommendations. *Educational Psychology Review, 20*, 463–467.

Shannon, C. E. (1951). Prediction and entropy of printed English. *Bell System Technical Journal, 30*, 50–64.

Snow, E. L., Allen, L. K., Jackson, G. T., & McNamara, D. S. (2014). Tracking choices: Computational analysis of learning trajectories. In J. Stamper, Z. Pardos, M. Mavrikis, & B. M. McLaren (Eds.), *Proceedings of the 7th international conference on educational data mining* (pp. 316–319). Heidelberg, Berlin, Germany: Springer.

Snow, E. L., Allen, L. K., Russell, D. G., & McNamara, D. S. (2014). Who's in control?: Categorizing nuanced patterns of behaviors within a game-based intelligent tutoring system. In J. Stamper, Z. Pardos, M. Mavrikis, & B. M. McLaren (Eds.), *Proceedings of the 7th international conference on educational data mining* (pp. 185–192). Heidelberg, Berlin, Germany: Springer.

Snow, E. L., Jackson, G. T., & McNamara, D. S. (2014). What do they do?: Tracing students' patterns of interactions within a game-based intelligent tutoring system. In J. L. Polman, E. A. Kyza, D. K. O'Neill, I. Tabak, W. R. Penuel, A. S. Jurow, K. O'Connor, T. Lee, & L. D'Amico (Eds.). *Learning and becoming in practice: The international conference of the learning sciences (ICLS) 2014* (Vol. 3, pp. 1481–1482). Boulder, CO: International Society of the Learning Sciences.

Snow, E. L., Jackson, G. T., Varner, L. K., & McNamara, D. S. (2013b). The impact of system interactions on motivation and performance. In *Proceedings of the 15th international conference on human–computer interaction (HCII)* (pp. 103–107). Heidelberg, Berlin, Germany: Springer.

Snow, E. L., Jackson, G. T., Varner, L. K., & McNamara, D. S. (2013a). The impact of performance orientation on students' interactions and achievements in an ITS. In C. Boonthum-Denecke & G. M. Youngblood (Eds.), *Proceedings of the 26th annual Flordia artificial intelligence research society (FLAIRS) conference* (pp. 521–526). Menlo Park, CA: The AAAI Press.

Snow, E. L., Jacovina, M. E., Allen, L. K., Dai, J., & McNamara, D. S. (2014). Entropy: A stealth assessment of agency in learning environments. In J. Stamper, Z. Pardos, M. Mavrikis, & B. M. McLaren (Eds.), *Proceedings of the 7th international conference on educational data mining* (pp. 241–244). Heidelberg, Berlin, Germany: Springer.

Snow, E. L., Likens, A., Jackson, G. T., & McNamara, D. S. (2013). Students' walk through tutoring: Using a random walk analysis to profile students. In S. K. D'Mello, R. A. Calvo, & A. Olney (Eds.), *Proceedings of the 6th international conference on educational data mining* (pp. 276–279). Heidelberg, Berlin, Germany: Springer.

Taylor, R. S., O'Reilly, T., Rowe, M., & McNamara, D. S. (2006). Improving understanding of science texts: iSTART strategy training vs. web design control task. In R. Sun & N. Miyake (Eds.), *Proceedings of the 28th annual conference of the cognitive science society* (pp. 2234–2239). Mahwah, NJ: Erlbaum.

Winters, F. I., Greene, J. A., & Costich, C. M. (2008). Self-regulation of learning within computer-based learning environments: A critical analysis. *Educational Psychology Review, 20*(4), 429–444.

Zhou, M. (2013). Using traces to investigate self-regulatory activities: A study of self-regulation and achievement goal profiles in the context of web search for academic tasks. *Journal of Cognitive Education and Psychology, 12*, 287–305.

Zimmerman, B. J. (1990). Self-regulated learning and academic achievement: An overview. *Educational Psychologist, 25*, 3–17.

Zimmerman, B. J. (2008). Investigating self-regulation and motivation: Historical background, methodological developments, and future prospects. *American Educational Research Journal, 45*(1), 166–183.

Zimmerman, B. J., Bandura, A., & Martinez-Pons, M. (1992). Self-motivation for academic attainment: The role of self-efficacy beliefs and personal goal setting. *American Educational Research Journal, 29*(3), 663–676.

Zimmerman, B. J., & Schunk, D. H. (1989). *Self-regulated learning and academic achievement: Theory, research, and practice*. Springer-Verlag Publishing.

Zimmerman, B. J., & Schunk, D. H. (2001). Reflections on theories of self-regulated learning and academic achievement. *Self-Regulated Learning and Academic Achievement: Theoretical Perspectives, 2*, 289–307.

Zimmerman, B. J., & Schunk, D. H. (2013). *Self-regulated learning and academic achievement: Theoretical perspectives*. Routledge.