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

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ABSTRACT

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.

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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;

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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 (Motiva-

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