Are You Committed? Investigating Interactions among Reading Commitment, Natural Language Input, and Students' Learning Outcomes

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ABSTRACT
The current study identifies relations among students' natural language input, individual differences in reading commitment, and learning gains in an intelligent tutoring system. Students (n = 84) interacted with iSTART across eight training sessions. Linguistic features of students' generated self-explanations (SEs) were analyzed using Coh-Metrix. Results indicated that linguistic properties of students' training SEs were predictive of learning gains, and that the strength and nature of these relations differed for students of low and high commitment to reading.

Keywords
Natural Language Processing, Learning, Intelligent Tutoring Systems, Reading Commitment

1. INTRODUCTION
Educational learning environments provide students with instruction intended to enhance particular knowledge, skills, and strategies in various domains. For example, iSTART is an intelligent tutoring system (ITS) that teaches students to use self-explanation (SE) reading strategies to comprehend challenging science texts. In this system, strategies are introduced and demonstrated to students. Then, students are offered the opportunity to practice applying the strategies they have learned to new texts. A natural language processing (NLP) algorithm assesses the quality of students' generated SEs and assigns scores (ranging from 0-3) and feedback to students during training [1].

Empirical studies have found that iSTART improves students' comprehension and strategy use over control groups at multiple education levels [2-3]. More recent work has investigated the impact of individual differences on students' learning gains in the system [4-5]. Jackson, Varner, Boonthum-Denecke, and McNamara (under review), for instance, found that iSTART helped students with low reading commitment to significantly improve their SE performance and ultimately match (or exceed) the performance of high commitment readers.

2. STUDY AND RESULTS
In the current study, we expand upon previous research to determine how individual differences in reading commitment impact students' natural language input and their subsequent learning gains. We employ NLP techniques to identify the linguistic properties of students' SEs that are predictive of learning gains. We then examine how these relations may differ for students with low and high prior reading commitment.

Participants were 84 high-school students randomly assigned to one of two versions of iSTART. Half (n = 43) of the students interacted with the original iSTART system and the other half (n = 41) interacted with a game-based version called iSTART-ME (motivationally enhanced) [6]. Both groups completed the same SE tasks and were assessed with the same algorithm; therefore, the conditions were collapsed for these analyses.

Students' learning gains were assessed using their SE scores (provided by the NLP algorithm) at pretest and posttest. To avoid biases associated with direct gain scores (low performing students have more room for improvement), a relative gain score was calculated. Relative gain scores represent students' improvement as a proportion of their possible improvement [(Posttest Proportion – Pretest Proportion) / (1 – Pretest Proportion)]. Additionally, students' reading commitment was assessed through demographic questions at pretest. Due to the limited scope available for this paper, the current analyses focus on a question that asked students to report the number of hours they spent reading for science courses; however, all reading commitment measures provided similar trends and results.

2.1 COH-METRIX ANALYSIS
Individual (sentence-level) SEs were combined for each text read and self-explained during training. This aggregation method is discussed in greater detail in previously published work [7]. Coh-Metrix [8] indices were calculated for each aggregated SE file. For each student, the mean values of 30 Coh-Metrix were calculated across texts to provide an average score for each linguistic measure. For more details on the linguistic measures presented here, please see [8].

2.2 ANALYSES
We investigated how linguistic properties of students' generated SEs predict relative learning gains. A stepwise regression analysis using each student's average Coh-Metrix scores as predictors of

their relative gain scores yielded a significant model, $F(2, 83) = 6.90$, $p = .002$; $R^2 = .15$, retaining two predictors: *Third Person Pronoun Incidence* [β = -28, t(1, 82)= -2.81, p = .01] and *Average Sentence Length* [β = .26, t(1, 83)= 2.51, p = .01]. Results of this analysis indicate that when students used third person pronouns (e.g., he, she, it) and short sentences in their SEs, they were less likely to improve after training. At a global level, this analysis indicates that the use of objective and less elaborate language led to lower gains in the system.

Analyses further investigated how linguistic properties may be predictive of relative gain scores as a function of students' prior commitment to reading. A median split on the pretest reading commitment measure (i.e., hours spent reading for sciences courses) was used to categorize students as having either low (n = 47) or high (n = 37) reading commitment.

A stepwise regression analysis using the average Coh-Metrix scores for *low reading commitment students* as predictors of their relative gain scores yielded a significant model with one predictor, $F(1, 46) = 6.33$, $p = .02$; $R^2 = .12$ (see Table 1). This result indicates that students with low reading commitment who repeated concepts across SEs tended to gain more from training.

Table 1. Stepwise Regression Analyses for Low and High Commitment Students

Linguistic Indices	β	ΔR^2
Low Reading Commitment		**.12***
Noun Overlap	.35	
High Reading Commitment		**.56****
Third Person Pronouns	-.45	.19*
Incidence of Infinitives	.47	.10*
Average Polysemy	-.45	.09*
Casual Ratio	.53	.11*
Incidence of Negations	-.32	.07*

p<.05 *, *p*<.001 **

A stepwise regression using the average Coh-Metrix scores for *high reading commitment students* as predictors of relative gain scores yielded a significant model with five predictors, $F(5, 36) = 7.77$, $p < .001$; $R^2 = .56$ (see Table 1). This analysis indicated that the linguistic properties of training SEs accounted for over half of the variance in high reading commitment students' learning gains. Most significantly, high reading commitment students benefitted most when they used less objective language within their SEs.

3. DISCUSSION

This study investigated relations among students' prior commitment to reading, linguistic properties of their generated SEs, and relative learning gains in the iSTART system. Results indicated that the relations between the linguistic features of students' SEs and relative learning gains varied when accounting for students' reading commitment. In particular, one cohesion variable accounted for 12% of the variance in low reading commitment students' relative learning gains, whereas five predictors combined to account for over 50% of the variance in the relative learning gains of highly committed students.[1] As mentioned previously, analyses with other reading commitment measures produced similar results.

[1] Separate analyses confirmed that these results could not be accounted for by individual differences, such as reading ability, as these measures were not predictive of relative learning gains.

This work expands upon previous research, relating features of natural language input to the level of students' cognitive processing of text [9]. The current analyses leverage this prior work to investigate how linguistic differences between groups of students shed light on their potential to gain from training. These results can help researchers gain a better understanding of the learning processes used by different student users, as well as the complex interactions between individual students and learning systems.

4. ACKNOWLEDGMENTS

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