Linguistic Content Analysis as a Tool for Improving Adaptive Instruction

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Abstract. This study investigates methods to automatically assess the features of content texts within an intelligent tutoring system (ITS). Coh-Metrix was used to calculate linguistic indices for texts (n = 66) within the reading strategy ITS, iSTART. Coh-Metrix indices for the system texts were compared to students' (n = 126) self-explanation scores to examine the degree to which linguistic indices predicted students' self-explanation quality. Initial analyses indicated no relation between self-explanation scores on a given text and its linguistic properties. However, subsequent analyses indicated the presence of robust text effects when analyses were separated for high and low reading ability students.

Keywords: Natural Language Processing, Readability, Tutoring, ITS, Text Characteristics, System Adaptability.

1 Introduction

Coh-Metrix [1] is a computational text analysis tool that was developed, in part, to provide stronger measures of text difficulty [2]. To account for multiple text dimensions, Graesser and colleagues (2011) developed the *Coh-Metrix Easability Components* [3]. These components offer a detailed glance at the primary levels of text difficulty and are aligned with an existing multilevel framework [4]. Additionally, Coh-Metrix offers general readability formulas (e.g., *Flesch-Kincaid Grade Level, FKGL)* as well as fine-grained linguistic indices that relate to lower and higher-level aspects of texts, from basic text properties to lexical, syntactic, and cohesive measures.

1.1 iSTART

iSTART trains adolescent students to use self-explanation (SE) and reading comprehension strategies [5]. Training in iSTART is divided into three modules: introduction, demonstration, and practice. In the modules, students receive instruction, watch demonstrations of SEs, and practice applying strategies to texts. iSTART scores students' SEs (from 0 to 3) using a natural language assessment algorithm [6] that utilizes a combination of word-based measures and latent semantic analysis. In iSTART, students have the opportunity to read and self-explain complex texts

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assigned by the teacher, experimenter, or system curriculum. One research goal has been to identify student characteristics and text features associated with performance [2], [7]. By doing so, our objective is to develop algorithms that intelligently guide text assignment and feedback during training.

2 Current Study and Results

We build upon previous work investigating reader characteristics, text difficulty, and students' performance. Our goal is to use readability and linguistic measures to identify interactions between student and text characteristics on SE performance.

Participants in the current study were 126 high-school students randomly assigned to one of two versions of iSTART. Half ($n = 65$) of the students interacted with the original iSTART system and the other half ($n = 61$) interacted with a game-based version called iSTART-ME (motivationally enhanced) [8]. In both conditions, students completed the same SE tasks and were assessed with the same algorithm; therefore, the two conditions were collapsed for the current analyses.

2.1 Global Analyses

The SE scores for each text were combined to produce a mean *text SE score*. Thus, each text had an overall mean SE score, which reflected the average score that all students received on that text. Further, Coh-Metrix was used to calculate text difficulty and linguistic measures for each content text.

Correlations between text SE scores and text difficulty measures indicated that text difficulty was not related to students' overall SE quality. Follow-up analyses were conducted for low and high reading ability students to examine the influence of text characteristics on SE quality. A median split on the pretest comprehension scores (Gates-MacGinitie) was used to categorize students as either low or high reading ability. Mean text SE scores were compiled separately to produce a mean score for low ability students and a mean score for high ability students.

2.2 Low Reading Ability Students

A stepwise regression analysis using the readability measures as predictors of SE scores yielded a significant model, $F(1, 58) = 6.01$, $p < .05$; $R^2 = .10$, retaining only one predictor: FKGL [$\beta = -.31$, $t(1, 58)= -2.45$, $p < .05$].

In addition to the standard readability measures, analyses examined which fine-grained linguistic properties interacted with reading ability to influence SE quality. A stepwise regression analysis was conducted on low ability students' SE scores from the battery of linguistic indices provided by Coh-Metrix; this yielded a significant model with four predictors, $F(4, 58) = 4.96$, $p < .01$; $R^2 = .27$ (see Table 1).

Table 1. Linguistic measures predicting self-explanation scores

Variable	*β*	SE *β*	B	ΔR^2
Final Model For Low Ability				**.27****
Logical Connectives	.44	.00	.01**	.07*
Average Syllables per Word	-.24	.29	-.57	.08*
MED (all words)	-.31	1.19	-2.90*	.06*
Agentless Passives	-.25	.01	-.02*	.06*
Final Model For High Ability				**.34****
Lexical Diversity	.28	.00	.00*	.17**
Modifiers per Noun Phrase	-.34	.20	-.62**	.10**
Logical Connectives	.29	.00	.01*	.08*

** $p < .01$; * $p < .05$

2.3 High Reading Ability Students

A stepwise regression analysis examining the six readability measures as predictors of SE scores yielded a significant model, $F(2, 57) = 6.23$, $p < .01$; $R2 = .19$, with two predictors: Deep Cohesion [$\beta = .39$, $t(1, 57)= 3.06$, $p < .01$, R^2 change = .08] and Narrativity [$\beta = .34$, $t(2, 57) = 2.65$, $p < .05$, R^2 change = .10].

A stepwise regression using the Coh-Metrix linguistic measures was significant and included three predictors, $F(3, 57) = 9.29$, $p < .001$; $R2 = .34$ (see Table 1). Thus, high reading ability students produce higher SE scores for texts with varied word choices, logically connected ideas, and simple syntax constructions.

3 Conclusions

The current study investigated a method for assessing text difficulty measures that showed significant relations to students' SE performance. Additionally, we examined whether these text effects differed for students with low and high reading skills. The results of our initial analyses suggested that characteristics of training texts had no effect on students' SE scores. However, when reading skill was considered, significant text effects were identified for low and high ability students. Low reading ability students benefited from lower grade level texts with simple words and explicit cohesive devices. Conversely, high ability students generated better SEs for texts that had explicit and deep cohesion, varied word choice, and simple syntax. Overall, these results suggest that automated indices of text difficulty can provide valid representations of system content, particularly using specific linguistic indices.

These results have implications for the development of adaptive content in computerized systems. This study indicated that text difficulty accounted for less variance in low ability students' SE scores than those of high ability students. Thus, low reading ability students may be affected by a number of non-linguistic factors not addressed in this study, such as text genre. Future studies should investigate methods for representing these features. Further, the results suggest that the analysis of text difficulty at multiple levels produced different results among the low and high ability students. Thus, developers of computerized learning environments may want to consider how to assess content at the appropriate level for individual students. Overall, these results, along with previous research, support the need for computerized systems to match characteristics of their users with characteristics of reading material. The current work provides a foundation on which to develop new methods that can intelligently adapt text types based on the needs of the readers.

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