Self-Explanation vs. Think Aloud: What Natural Language Processing Can Tell Us

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Abstract

Self-explanation is designed to increase coherence by encouraging students to activate prior knowledge, generate inferences, and make casual connections (McNamara, 2004). The current study used natural language processing to examine how readers' responses differ when instructed to self-explain or think aloud. Self-explanations were found to contain more cohesion, semantic overlap, and causal, active, and positive emotion words than think-alouds. The results provide evidence that instructional differences significantly predicted linguistic differences reader's responses to texts.

Keywords: Natural language processing, Self-Explanation, Think-Aloud

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To achieve successful comprehension, readers must develop and maintain a coherent mental representation of the text. This representation then comprises the reader's developing understanding of what the text is about (e.g., Glenberg, Meyer, & Lindem, 1987). It contains both information explicitly stated in the text and information related to the text from readers' prior knowledge.

Assessing the nature of readers' mental representation has provided valuable insight into the processes that support comprehension. For example, researchers have collected readers' constructed responses to gain information about the nature of the representation. Analysis of these responses has exposed the role of readers' strategies, processes, and knowledge involved in achieving comprehension (Millis & Magliano, 2012).

Natural language processing (NLP) offers the opportunity to more fully analyze the linguistic features of student responses across multiple dimensions. By examining readers' constructed responses for the presence of linguistic features that contribute to the successful comprehension of texts, NLP tools provide a deeper understanding of online comprehension processes involved in the development of a coherent mental representation (McNamara et al., 2014). For example, the level of cohesion (or overlap between information in the text—a proxy of coherence) present in students' constructed responses predict reading comprehension ability (Allen, Snow, & McNamara, 2015).

Using NLP to examine readers' responses to text can also provide insight into the influence of task instructions upon comprehension, such as self-explanation. Self-explanation, a strategy in which students explain previously read information to themselves, is designed to capitalize on the importance of prior knowledge and increase coherence of the reader's mental model. It encourages students to activate prior knowledge, generate inferences, and make causal connections among ideas in text, which benefits comprehension (McNamara, 2004).

The goal of the current study was to use NLP methodologies to investigate the differential effects of self-explanation or think-aloud instructions on the linguistic features of reader's constructed responses when reading multiple texts. The current study specifically examined how features of cohesion, lexical choices, and sentiment choices differed across instruction type.

Method

As part of a larger study, undergraduate participants ($n = 151$) were asked to read four texts about global warming. During reading, they were instructed to either self-explain ($n = 68$) or think-aloud ($n = 83$). Students then completed comprehension assessments, including sentence, within-text inference, and across-text inference verification tests. Students also completed a timed, argumentative essay, prior knowledge measure, and demographic questionnaire.

NLP tools were used to examine linguistic features in students' constructed responses when readers were instructed to self-explain or think aloud. Specifically, TAACO (Crossley, Kyle, & Dasculu, 2019; Crossley, Kyle, & McNamara, 2016), SEANCE (Crossley, Kyle, & McNamara, 2017), and TAALES (Kyle & Crossley, 2015; Kyle, Crossley, & Berger, 2018) were used to investigate the differential effects of instruction on cohesion, lexical choices, and presence of sentiment in students' responses.

Key Findings

Constructed responses in the self-explanation condition were generally more cohesive than those in the think-aloud condition across a number of indices: *all connectives,* $t(147.76) = -$

2.90, $p < .05$); *causal connectives,* $t(144.65) = -3.12$, $p < .05$; *reason and purpose connectives* $t(130.60) = -2.50$, $p < .05$; *noun overlap* at the *local level*: $t(95.26) = -8.58$, $p < .001$; and *global level*: $t(90.14) = -7.30$, $p < .001$; *verb overlap* at the *local level*: $t(109.66) = -2.48$, $p < .05$; and *global level*: $t(108.23) = -3.39$, $p < .001$; and *semantic cohesion,* $t(147.99) = -8.05$, $p < .001$. Additionally, constructed responses in the self-explanation and think-aloud conditions also differed in lexical and sentiment choices. Self-explanations contained more *causal words* ($t(143.49) = -6.94$, $p < .001$), *active words* ($t(147.97) = -2.54$, $p < .05$), and *positive emotion words* ($t(136.7) = -2.88$, $p < .01$) than think alouds, which contained more *passive words* ($t(135.09) = 3.13$, $p < .01$) and *negative emotion words* ($t(148.00) = 2.33$, $p < .05$).

These findings support the notion that self-explanation promotes coherence building processes during reading comprehension. These analyses indicate that readers instructed to self-explain are more likely to build causal and semantic cohesion than readers asked simply to think-aloud. Additionally, there were more active and positive emotion words when readers were asked to self-explain, potentially suggesting that self-explanation prompted individuals to focus on different aspects of the textual information.

Discussion

Taken together, these findings support previous work indicating that instructional differences during reading significantly predicted linguistic differences in student's responses to texts. Furthermore, they demonstrate that NLP can be used to detect differences in readers' processing of multiple complex texts. The amount and type of linguistic features present in students' constructed responses, measured through NLP, can provide insight into online reading comprehension processes and the nature of readers' mental representations.

Table 1. Descriptive Statistics [Mean (*sd*)] for linguistic and semantic NLP indices

Index	Self-Explanation	Think Aloud	*d*
Connectives	.073 (.014)	.066 (.019)	-.419
Causal connectives	.030 (.011)	.024 (.012)	-.521
Reason & Purpose	.015 (.009)	.012 (.008)	-.354
Sent. overlap (nouns)	.560 (.330)	.177 (.174)	-1.452
Para. overlap (nouns)	.853 (.617)	.254 (.295)	-1.239
Sent. overlap (verbs)	.419 (.356)	.294 (.235)	-.414
Para. overlap (verbs)	.894 (.762)	.529 (.493)	-.569
Casual Words	.058 (.014)	.041 (.015)	-1.717
Active Words	.152 (.019)	.143 (.025)	-.405
Passive Words	.083 (.012)	.092 (.021)	.526
Positive Emotion Words	.060 (.016)	.053 (.015)	-.451
Negative Emotion Words	.033 (.011)	.037 (.014)	.318
Semantic Cohesion	.190 (.012)	.171 (.015)	-1.399

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