Research paper

The Utility of Coh-Metrix Application for the Selection of Core Texts: Trialling of Texts for Students of Computer Sciences

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Abstract

Measurement assuredly lends more objectivity and reliability to textbook evaluation and selection and enables it to provide a lens into the actual effect of how teachers use an ELT textbook on the academic literacy of learners. This paper reports a trial project for computation of cohesion metrics of ESP texts for Iranian students of computer sciences. The project first shaded light on some inadequacy of the text selection rubrics within the paradigm of text-driven materials development problematizing the subjective, intuitive, impressionistic criteria for the selection of the core text. Then it raised two questions. They asked what enables achievement of the multi-dimensional mental representation of texts on the part of the target learners and how it is accomplished. Third, it introduced a utility application called Coh-Metrix that was developed to compute instantly and automatically cohesion ad readability indices. Forth, it put to test some existing ESP text for students of computer sciences for cohesion indices in order to make a tentative comparison with some grade level 6 science text against cohesion metrics. Lastly and never to be least, it concluded that explicit cohesive characteristics of texts enable the achievement of multidimensional mental representation of the text by selection and assignment of a core text cohesive enough using some objective metrics. Iranian EFL teachers and materials developers can, by implication, employ objective measures as they are evaluating and selecting core texts.

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Introduction

It is unequivocal that text as a context is not only the point of departure for the text selection process but it is also a pivot around which everything comes after it revolves. It means that whatever learners and teachers do is determined organically by interaction with such text rather than by a syllabus or content map.

For Tomlinson (2003), an authentic text is to drive the unit of materials instead of predetermined teaching points. The principled text-driven framework for materials development is the Tomlinson's preferred framework. It consists of ten stages one of which is the selection of a core text potentially capable of engaging the target learners affectively and cognitively (Tomlinson & Masuhara, 2019). Since the materials are to be principally driven by the text this stage is very important and should be criterion-referenced.

The criteria for core text selection might be implied, i.e. intuitive, or explicitly stated. For instance, Tomlinson (2003) sets as the criteria for text selection the following ones: the likelihood of the linguistic and cognitive levels of the text presenting an achievable challenge to the target learners and the likelihood of the target learners being able to achieve multidimensional mental representation of the text. If the core text is not checked quantitatively for explicit cohesive characteristics, it will fail to enable readers/learners to achieve multidimensional mental representation of it.

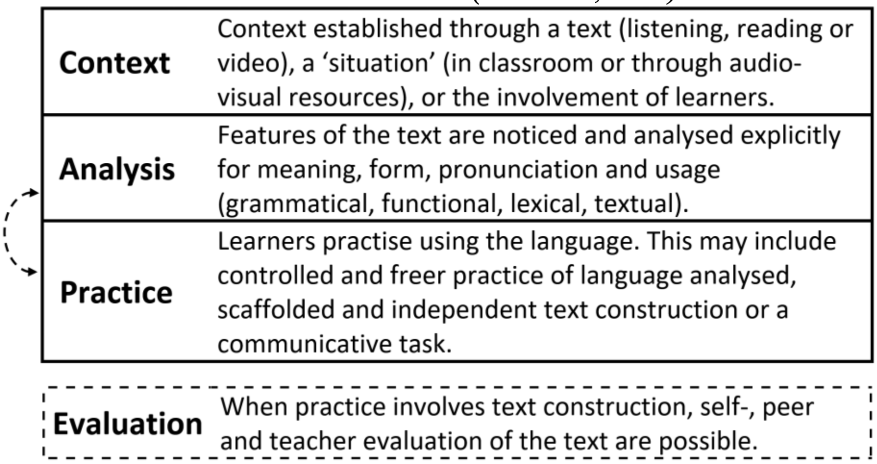
The study first threw some light on deficiencies of the text selection rubrics within the paradigm of text-driven materials development. In other words, it problematized the intuitive, impressionistic criteria for the selection of the core text when it comes to the non-native and less experienced teachers and materials writers. Second, acknowledging the need for objective measures for the selection of text in favor of the reader's achievement of multidimensional mental representation of the text, it raised two questions. Then, it proposed a solution to compensate for the deficiencies, i.e. some objective cohesion metrics. Moreover, a utility application called Coh-Metrix was introduced for the purpose of analyzing texts and producing many indices of the discourse and linguistic representations of a text. Besides, a tentative comparison was made between a sample ESP text and some grade level 6 science text using output cohesion indices from the application. Finally, the research questions were answered.

Literature Review

In contrast to several critiques of contemporary global ELT coursebooks (Tomlinson & Masuhara, 2013), Anderson's (2017a) analysis of such books indicates, since 2000, units of study do not typically follow a Presentation-Practice-Production (PPP) structure, as was more common in the 1980s and 1990s. Instead, they follow a context–analysis–practice (CAP/CAPE) structure— evaluation being an optional part—that involves first a written or aural text (frequently seeded with a specific, usually grammatical, feature) that is listened to or read at the beginning for meaningful comprehension, followed by analysis of the feature in question, and then practice that may or may not include both the controlled practice (e.g. ‘gapfill’ cloze exercises) and the freer production of the PPP model (see Figure 1).

Figure 1

The CAP/CAPE model (Anderson, 2020)

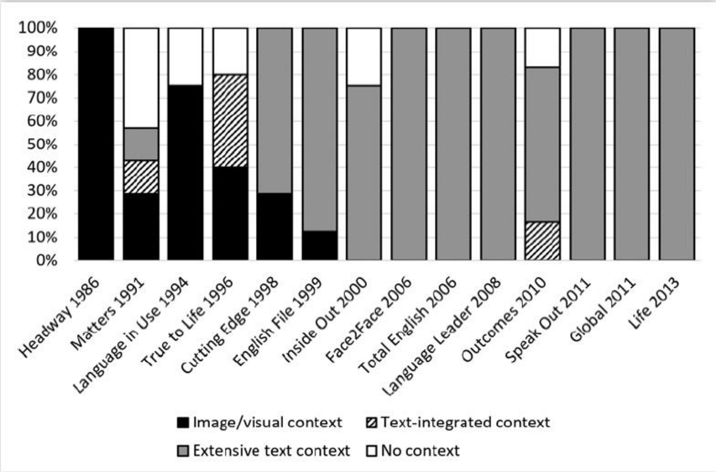


The Tomlinson and Masuhara’s (2013, p. 247) statement that more recent coursebooks only ‘deviate slightly’ from PPP model undermines the thematic integrated skills approach—commonly used today—and the potential benefit of pre-analysis exposure to featured text that may effectively foster receptive acquisition of grammar and lexis. According to the analysis mentioned above, the CAP paradigm is the most common instructional model in contemporary weak version of CLT. It is not considered as a normative prescription for how to teach, rather as a description of a current tendency.

Based on the dominant CAP(E) model, context can be set up through these three possibilities: a text, a situation, or the involvement of learners. Whether by chance or constraint-driven, the model has given rise to the text-driven framework for materials development, and as a result, to extensively text-based language teaching and related curriculum models common in academic contexts. Figure 2 shows clearly this tendency in percentile statistics.

Figure 2

Pre-analysis Context Types in First Editions of Global ELT Coursebooks from 1986 to 2013 (Anderson, 2020)



The kernel of the text-driven model for materials development is definitely a core text. For materials developers, including teachers, to make optimum selection of core texts, text evaluation is of service to identify its weaknesses and strengths.

Textbooks, in the eyes of Swales (1980), represent a problem at best, and are examples of educational failure at worst. While the significance of textbook in language education—for both general and specific purposes—has been increasingly recognized, textbook evaluation, however systematically conducted, is not robust enough especially in the practical fields. Hutchison and Waters (1987) assert that textbook evaluation is a straightforward analytical matching process, that of needs to solutions at hand. Mcdonough and Shaw's (2003) model, Breen &Candlin's (1987) model, and Cuningsworth's (1995) model are the most famous three models which just present questions and checklists based on various criteria for the administrator or teacher, as evaluator, to choose from (Zhao & Zheng, 2006). Although some researchers (e.g. Mukundan & Ahour, 2010) consider textbook evaluation checklist as a facilitator in the materials selection process, as Sheldon (1988, p. 245) put, 'coursebook assessment is fundamentally a subjective rule-of-thumb activity and that no neat formula grid or system will ever provide a definite yardstick'. For ELT textbook selection, pre-use evaluation is of use because, through referencing adapted criteria or self-made, evaluators could rapidly get an impression of the possible effect of an ELT textbook on the academic literacy of learners (Tomlinson, 2003; Guilloteaux, 2013; Mashura & Tomlinson, 2013). For Ellis (1997), predictive, pre-use evaluation of textbooks helps teachers select the most suitable textbook for a particular language classroom by taking into account its likely performance. However, it is an initial process that only allows the evaluator to make impressionistic judgments of the effect of a textbook (Guilloteaux, 2013; Tomlinson, 2003).Therefore, textbook evaluation should make use of measurement rather than prediction to be more objective and reliable and able to provide a lens into the actual effect of how teachers use an ELT textbook on the academic literacy of learners. English textbook evaluation systems are traditionally based on qualitative analysis. In other words, they involve so many subjective individual judgments so that their results are unavoidably not authentic. Mukundan and Ahour's (2010) review of the evaluation checklists revealed that they are mostly qualitative. The downside of English textbook evaluation has been the inadequacy of quantitative analysis.

It is due to a shortage of effective tools and methods. Thus the challenges of present textbook evaluation consist of how to set more quantitative criteria to evaluation system, how to make the evaluation of textbook more objective, and how to make it easier to be functional (Yang, Wang, & Wen, 2008).

Likewise, core text selection as the first stage of the Tomlinson & Masuhara's (2019) materials-development framework is badly in need of some more objective indices or metrics. There are reasonable grounds for both teachers and materials writers to use more solid, objective ways to investigate the cohesion of the text. First, the researcher believes that such criteria as stated by Tomlinson (2013b) for core text selection allow merely for subjective, intuitive, impressionistic ranking and evaluation of texts though it is done on a 5-point scale—that is categorically considered quantitative (Mukundan & Ahour, 2010)—and excludes any text that fails to achieve at least 4 on each of the criteria above. Second, these rubrics might work for native or experienced teachers and materials writers, and other practitioners—non-natives and the less experienced—might be in trouble using them as to select appropriate texts (Mukundan & Ahour, 2010). Due to these deficiencies, this study was to investigate and introduce cohesive indices as well as readability index as objective measures that could aid teachers and materials writers in selecting and scaling texts in addition to intuitive criterion-oriented schemes. In doing so, it managed to address the following questions:

1. What is it that enables the target learners to achieve multidimensional mental representation of the text?
2. How could the target learners be able to achieve multidimensional mental representation of the text?

The first question intended to identify what is the main enabler that potentiates the target learners for making mental representation of the text. Besides, the second question aimed to describe how enabling process is realized.

Prior to answering the questions raised, two important aspects of texts have to be taken into consideration: cohesion and coherence. Graesser et al. (2003) define cohesion as "characteristics of the explicit text that play some role in helping the reader mentally connect ideas in the text." The definition of coherence is not that straightforward. It is a controversial subject. While the coherence of a text refers to the interaction between linguistic representations and knowledge representations, cohesion can be defined as characteristics of the text that are likely to facilitate the interaction of such processes, i.e. coherence.

Method

The research method of current project was of descriptive kind. It was a research in and with Coh-Metrix, i.e. an evaluative description of the utility of this program in selecting core texts. It attempted to gauge cohesion and coherence metrics of some text of the existing ESP textbook for students of computer sciences published by Payam Noor University. These metrics are definitely readability and easability indices: word concreteness, syntactic simplicity, referential cohesion, causal cohesion, and narrativity.

Instruments

Instruments included Coh-Metrix application and some input text as described below.

Coh-Metrix application

The need for some objective metrics can be satisfied by means of the most recent, advanced computer technologies. One of these software artifacts is Coh-Metrix application (Coh-Metrix henceforth) developed by Arthur C. Graesser and Danielle S. McNamara. It is a computational utility tool that analyzes texts on many different features and produces indices of the linguistic and discourse representations of a text. In other words, it is capable of computing cohesion and coherence metrics for written and spoken texts. As such, Coh-Metrix allows materials writers, educators, and researchers to instantly gauge the difficulty of written text for the end users, i.e. target learners.

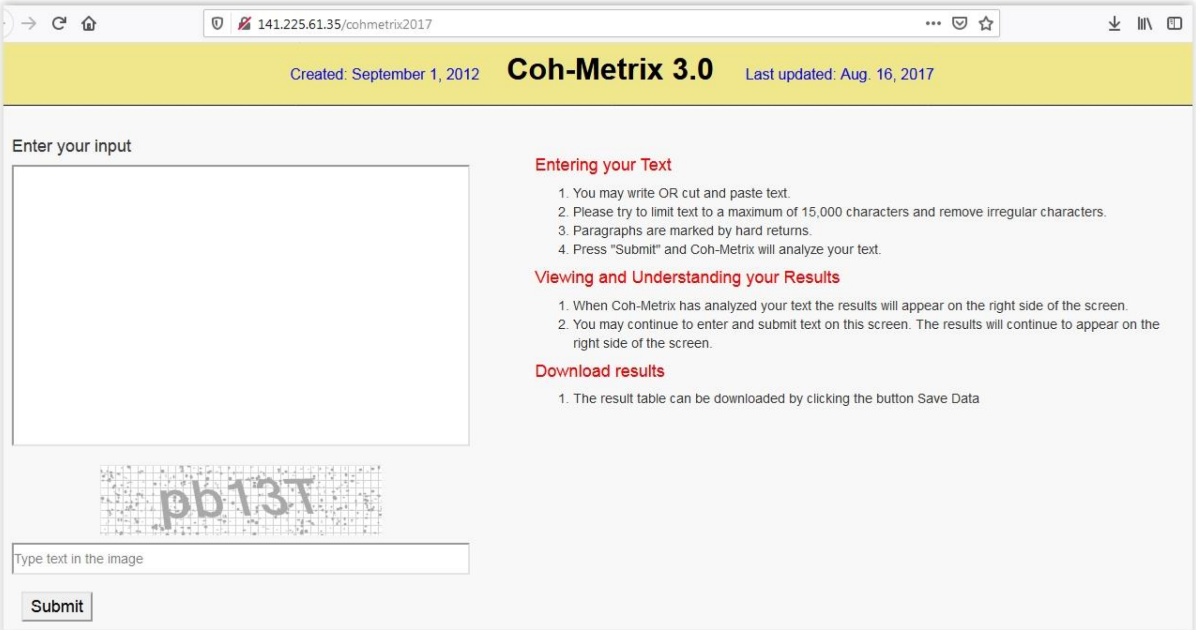
Graesser et al. (2011) figured out 5 main factors that account for most of the variance in texts across grade levels and text categories: word concreteness, syntactic simplicity, referential cohesion, causal cohesion, and narrativity. This finding can surely inform or contribute to the more objective selection of appropriate texts. The researcher is of the view that these factors can be considered as objective criteria for the selection of core text. They can be computed automatically and instantly using Coh-Metrix. Furthermore, the Coh-Metrix Reading Index performs significantly better than traditional readability formulas: the commonly used readability indexes (e.g., Flesch–Kincaid) were inappropriately distinguished between high and low-cohesion texts.

Input text

The input text was some ESP text taken from one of the existing ESP textbooks for students of computer sciences (Unit 8, English for Computer Engineering, Yousefkhani et al. (1385), Appendix A).

Data analysis procedure

To compute text indices and statistics, including cohesive indices and readability index, the input text was inserted into the designated space on the Coh-Metrix webpage which its address is shown in the address bar of the following picture.



Then, it is delivered to the application by pressing the Submit button. After submission, the Coh-Metrix takes a little time to analyze the input text and return the results—i.e. text indices and statistics—on the right side of the screen. The results table can also be saved for later use.

Results

As you inter the text of concern into the left largest box as well as the string of characters that has been appeared on the page into the field underneath, and push the ‘submit’ button, the application returns a table of data as shown in Appendix B. The table is made of 5 column and 106 rows. The rows are classified into 9 groups called *banks*. Each bank describes a group of mathematically or conceptually similar measures or indices. For example, rows PCNAR, PCSYN, PCCNC, PCREF, PCDC, PCVERB, PCONN, and PCTEMP form Text Easability Principal Component measure. As regards the columns, the first one shows the numbers assigned to rows. The second and third columns, headed label, include abbreviations of the indices that are actually some strings made of two parts. The first part comes from the measure title and utmost right part is the tag of the indices.

The forth column shows the scores and the last one provides a full description of the tag. The full returned table for the analysis of the text under study (Unit 8, English for Computer Engineering, Yousefkhani et al. (1385), Appendix A.) is shown as Appendix B. The easability components of the intended text are included in Table 1 and its readability index in Table 2. They are the most important linguistic and discourse characteristics that will be explained in the following section.

Table 1

The Text Easability Measures: Z-Scores and P-Scores

#	Measures	*z*-scores	*p*-scores
1	PCNAR	-0.391	34.830

2	PCSYN	-0.308	38.210
3	PCCNC	-0.782	21.770
4	PCREF	-0.658	25.780
5	PCDC	1.581	94.290
6	PCVERB	-0.703	24.200
7	PCCONN	-2.318	1.040
8	PCTEMP	1.146	87.290

Table 2

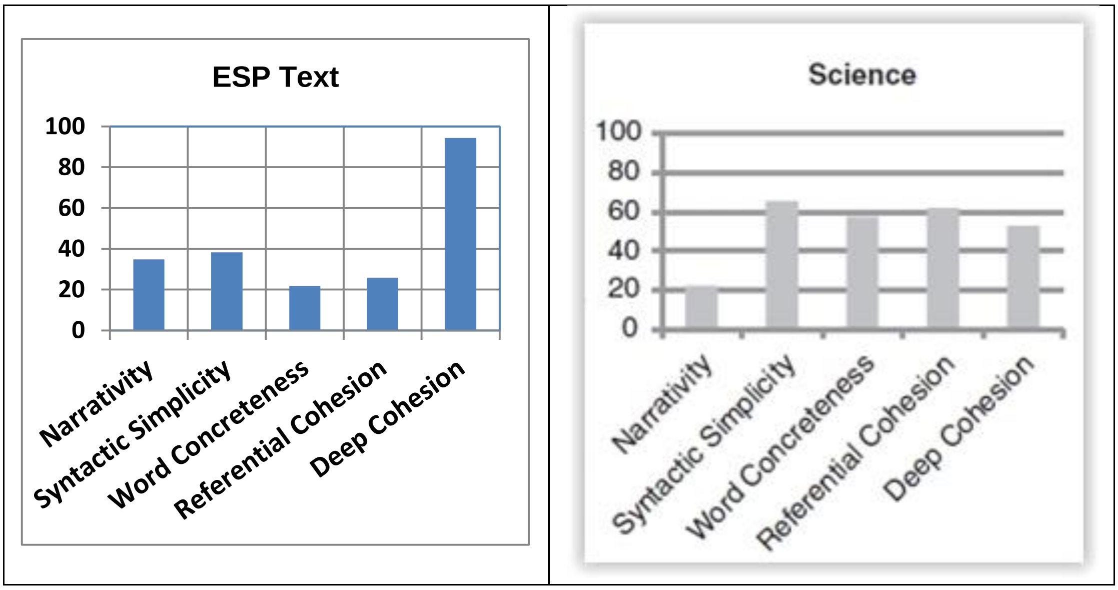
The Readability Measures

#	Measure	Readability
104	RDFRE	48.904
105	RDFKGL	11.673
106	RDL2	16.098

Figure 3 displays differences between ESP input text and upper grade level 6 science text in terms of easability percentile scores.

Figure 3

Differences in Easability Percentile Scores between ESP Input Text and Upper Grade Level 6 Science Text



Discussion

Discussion of the Coh-Metrix returned output is confined to two sets of numbers: 12-27 and 104-106 as sequenced in the output. In this section, first the former set which refers to the Coh-Metrixeasability components is discussed. Then, the latter set which deals with the readability measures is explored. Third, ESP input text and some upper grade level 6 science text are tentatively compared. Finally, the questions are answered according to the analyses and interpretations.

Coh-Metrixeasability components

The primary motivation for the development of Coh-Metrix was or is to provide not only better measures of text difficulty transcending traditional measures of readability that merely focus on surface characteristics of texts but also the specific sources of potential challenges or scaffolds within texts at the word and sentence levels as well as deeper levels of language. To that twofold end theories of discourse and text comprehension are to inform Coh-Metrix.

Research on and with Coh-Metrix leads to a deeper understanding of how texts differ and which indices are most reliable in detecting these differences at meaningful, consequential levels. The Coh-Metrixeasability components were developed as an outcome. These components better depict text ease (and difficulty) that emerge from the linguistic characteristics of texts. So as to discover what aspects of texts constitute text complexity, a principal components analysis (PCA) is carried out to reduce the large multivariate database—the TASA corpus—to fewer functional dimensions. Eight components accounted for a substantial 67.3% of the variability among texts. These components are remarkably in line with the multitier theoretical framework. Coh-Metrix 3.0 outputs these eight components in the *z*and *p* score forms. A *z*-score as a standard score indicates how many standard deviations an observation or datum is above or below the mean, where the mean is set at 0. A *p*-score (i.e. a percentile score) varies from 0 to 100%, with higher scores meaning the text is probably easier to read than other texts in the corpus. For instance, a percentile score of 80% implies 80% of the texts are more difficult and 20% are easier. The eight components are as follows (McNamara, et al., 2014, pp. 85-86). They are included in Table 1 as well.

1. *Narrativity* (12. PCNARz& 13. PCNARp). Narrative tells a story embracing characters, places, events, and things with which the reader is already familiar. Narrative is highly affiliated with everyday oral conversation. This rich component is closely associated with world knowledge, oral language, and word familiarity. Non-narrative texts lie at the other end of the continuum because they deal with less familiar topics. (For more elaboration on the first five components see following descriptions as well as the researchers' tentative comparison of the ESP input text and some grade level 6 science text.)

2. *Syntactic Simplicity* (14. PCSYNz& 15. PCSYNp). This component reflects the degree to which the sentences within the text contain fewer words and use simpler, familiar syntactic structures that are less challenging to process. At the other end of the continuum are texts that contain sentences with more words and that use complex, unfamiliar syntactic structures.

3. *Word Concreteness* (16. PCCNCz& 17. PCCNCp). Texts containing content words that are meaningful and concrete and induce mental images are more easily processed and understood. Abstract words typify concepts that are difficult to visualize. Therefore, texts that contain more abstract words are more challenging to understand.

4. *Referential Cohesion* (18. PCREFz& 19. PCREFp). A text with high referential cohesion contains words and concepts that overlap across sentences and the entire text, forming explicit

threads that connect the text for the reader. Typically, low-cohesion text is more difficult to process because there are fewer connections that tie the ideas together for the reader.

5. *Deep Cohesion* (20. PCDCz& 21. PCDCp). This measure displays the extent to which the text includes intentional and causal connectives when there are logical and causal relationships within the text. Such connectives enable the reader to form a more coherent and deeper understanding of the causal actions, processes, and events in the text. When a text contains many relationships but doesn't contain those connectives, the reader must infer the relationships between the ideas within the text. When the text is rich in deep cohesion, those relationships and global cohesion are easily understandable.

6. *Verb Cohesion* (22. PCVERBz& 23. PCVERBp). This component reflects the degree to which there are overlapping verbs within the text. When there are repeated verbs, the text likely includes a more coherent event structure which will facilitate and enhance situation model understanding. This component score is presumably more relevant for texts intended for younger readers and for narrative texts. Evidence for the significance of verb cohesion can come from McNamara, Graesser, and Louwerse (2012). It hypothesized that verb cohesion would be more significant for texts for younger readers since events and actions would be more influential in these texts than would objects. For instance, a text such as "Horses eat hay. Chickens eat grain. Mice eat cheese" has perfect verb overlap as expected. Its results suggested that the lower referential cohesion inherent in the lower-grade-level texts may be partially made up for by greater verb cohesion, more frequent words, and shorter sentences.

7. *Connectivity* (24. PCCONNz& 25. PCCONNp). This component reflects the degree to which the text contains explicit adversative/contrastive, additive, and comparative connectives to indicate relations in the text. This component reflects the logical relations count in the text that are explicitly conveyed. This score is probably related to the reader's deeper understanding of the relations in the text. Connectives as a whole play a significant role in the formation of cohesive links between ideas and clauses and provide clues about the organization of text. To find the difference that connectives may make in comprehension of text, Cain and Nash (2011) investigated the influence of them on young readers' processing and comprehension of text.

8. *Temporality* (26. PCTEMPz& 27. PCTEMPp). Texts containing more cues about temporality as well as having more consistent temporality (i.e., aspect, tense) are more easily processed and understood. Furthermore, temporal cohesion contributes to the reader's situation model level understanding of the events in the text. Zwaan and Radvansky (1998) verified that temporality plays a critical role in making a coherent mental representation of events unfolded in texts in general and in narrative texts in particular. Moreover, Duran, McCarthy, Graesser, and McNamara (2007) investigated temporal cohesion across narrative, history, and science text genres. Their discriminant analysis showed that the temporal cohesion indices were able to categorize texts reliably enough as belonging to a certain genre. The results indicated that while history and narrative texts were more similar in terms of temporality, narrative and science texts were most different. Narratives texts contained more temporal adverbial phrases

than history texts which, in turn, contained more such phrases than science texts. History and science texts also contained less positive temporal connectives than did narratives. This implies that temporal connective and temporal adverbial phrases are stylistic markers of narration. As expected, the present tense count was higher in science texts than in both history and narrative texts since science is apt to express timeless, generic facts whereas stories usually tell of past events.

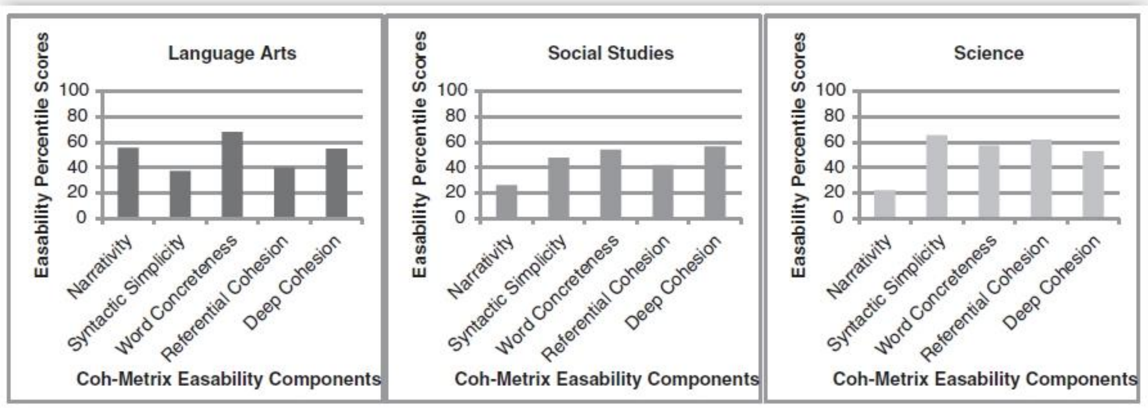
The first five of the above list (Narrativity, Syntactic Simplicity, Word Concreteness, Referential Cohesion, and Deep Cohesion) accounted for 54% of the variance. As a result, they have been incorporated within a tool or measure intended for educators, called Coh-Metrix text easability components. They are most directly associated with the ease of a text and account for the largest portion of the variance among the texts under analysis. They are also known as dimensions of text easability.

Coh-Metrix provides both percentile scores (p-scores) and z-scores as measures of easability. Noteworthy, the relationship between these two sets of scores is not linear. The percentiles are easier to understand, particularly in a graphic sketch.

The easability scores enable us to visualize differences between text genres. Figure 4 provides the five main Coh-Metrixeasability scores for a subset of language arts, social studies, and science texts above grade level 6 (based on traditional readability formula cutoff score of 55.99) from the TASA corpus.

Figure 4

Differences in Easability Percentile Scores between Text Genres (McNamara et al., 2014, p. 88)



As the graphs verify, the language arts texts tend to have higher narrativity than do the social studies or science texts. It means they use more familiar words combined with a tendency to focus on events and characters rather than objects and ideas. On the other hand, science texts and social studies have a greater density of information and thus lower narrativity. Passages low in narrativity potentially leave the reader unscaffolded by world knowledge. So students' prior domain knowledge should be taken into account. Since high narrativity scaffolds reading comprehension by providing more familiar text, the importance of transitioning readers toward less narrative text is to be recognized (therefore, in EFL academic contexts, the narrativity scores should be taken into account when developing textbooks for general English and ESP textbooks for ensuring a safe, smooth transition). Developing readers must learn to understand increasingly complex and unfamiliar ideas. If a teacher wishes to move the student toward learning to use knowledge and generating inferences to understand more challenging text, s/he may consider where the text falls on the spectrum of narrativity in terms of the Coh-Metrixeasability scores. Figure 4 also verifies that science and social texts are informational texts that are low in narrativity. They are lower in word concreteness because informational texts need, in essence, to include more abstract concepts than do language arts texts.

Coh-Metrix readability measure

In this section the researcher deals with approaches that exist for objectively selecting and grading texts using readability formulas.

Approaches to scaling and selecting texts

There are two approaches to scaling and selecting texts: unidimensional and multidimensional. The traditional unidimensional approach lends itself to unidimensional representations of comprehension ignoring the importance of readers' deeper levels of understanding. It is to have a single metric of text ease or difficulty. Traditional readability measures focus on superficial characteristics of text related to readers' understanding of the words and of individual sentences in the text. In line with them, cloze tasks/tests are most often used to gauge individuals' reading levels, and these tasks/tests by their very nature assess comprehension primarily within sentences based on word associations. They depend primarily on decoding rather than language comprehension skills. Hence, traditional readability measures do not tap readers' ability to comprehend global levels of discourse meaning.

There are many traditional readability formulas. Coh-metrix provides three of them: Flesch Reading Ease (RDFRE), Flesch-Kincaid Grade Level (RDFKGL), and L2 Readability (RDL2). The first two rely primarily on the length of words and sentences within the text, and are computed, in Coh-Metrix, as follows:

RDFRE = [206.835 – (1.015 * sentence length) – (84.6 * word length)]

RDFKGL = [(0.39 * sentence length) + (11.8 * word length) – 15.59]

Where,

Sentence Length (DESSL) = the mean number of words per sentence in a text,

Word Length (DESWLsy) = the mean number of syllables per word (which is highly correlated with the mean number of letters).

Third readability formula, termed L2 Readability (RDL2), results from the exploration of unidimensional metrics of text readability. It aims to specifically predict the readability of texts for second language readers. This formula not only takes text challenges at the sentence and the word level into consideration, but it also considers the cohesion between sentences in the text. Crossley, Salsbury, McCarthy, and McNamara (2008) reported the L2 Reading Index as in the following formula:

RDL2 = -45.032 + (52.230 * CRFCWO1) + (61.306 * SYNSTRUT) + (22.205 * WRDFRQmc)
Where, CRFCWO1 = the score of row #34, SYNSTRUT = the score of row #73, and WRDFRQmc = the score of row #94

The Coh-Metrix L2 Readability formula correlated 0.93 with the Japanese students' cloze test performance on the academic instructional reading passages from biology, chemistry, civics, current affairs, economics, geography, history, literature, mathematics, and physics. It is significantly great comparable to those of the two Flesch and one of the Miyazaki EFL readability index which were respectively 0.85 and 0.86. As a result, RDL2 provides a significant improvement in predicting cloze performance by L2 readers on academic texts. The L2 Readability formula can be further assessed in terms of its ability to predict either L2 or first language readers' comprehension of texts. Crossley et al. (2011) compared the L2 Readability formula to the two Flesch scores in their ability to classify texts that are typically read by L2 readers. Usually texts for language learners are adapted or simplified in various ways to make them more ZPD-conformed and comprehensible to the readers. Material developers who are adapting texts often follow guidelines on word lists or use traditional readability formulas as mentioned above. The other way around is for materials developers and teachers to follow intuitive approaches driven by the editor's sense of text comprehensibility or by their own intuitions as Tomlinson points to. Crossley et al. (2011) compared the three readability formulas' ability to classify 300 L2 news texts that had been simplified by an independent group of authors at the beginning, intermediate, and advanced levels using intuition and without word lists or readability formulas. These news texts were typically selected for their nonacademic interest value. They found that the L2 formula was the best predictor of grade level classification, correctly classifying 59% of the reading texts by level overall. It classified the beginner and advanced texts 70% accurate and the intermediate texts 39% accurate since this category of texts contains features from both categories. It is worth noting that the two Flesch indices served very poorly, with average accuracies ranging between 44% and 48%. As such, these findings verified the advantages of the Coh-Metrix L2 Reading Index in classifying and examining differing levels of intuitively simplified texts over at least two traditional readability formulas.

Apart from traditional readability formulas, another approach to estimating the readability of texts is to predict the publisher-assigned grade level of textbooks. In a study, Dufty, Graesser, Louwerse and McNamara (2006) took samples of texts which their publishers had already assigned grade level to them either through a complex mix of quantitative indices or the intuition of expert judgment. They examined the degree to which Coh-Metrix successfully predicted these assigned grade levels. They found that Flesch Kincaid Grade Level correlated 0.77 with grade level, and that cohesion as measured by LSA (latent semantic analysis) sentence to text similarity correlated –.53. The findings suggest that cohesion in combination with Flesch-Kincaid explains 68% of the variance in the grade level of the textbooks. It implies that that cohesion, in particular in combination with Flesch-Kincaid Grade Level, can predict publisher-assigned grade level better than either readability alone or cohesion alone. As regards cohesion variables, three of them significantly contributed: LSA sentence to text, incidence of causal verbs, and the incidence of causal connectives. Therefore, Dufty et al. (2006) empirically support the assumption that cohesion has an important role to play in the evaluation of text difficulty.

Unidimensional representations of comprehension have their own pros and cons. A unidimensional representation is assumed by readability formulas. A single dimension of text difficulty is simple enough to be used by teachers assigning texts for students to read and makes it easier for teachers to select texts at the appropriate level of challenge. A unidimensional metric constitutes a simple solution to the task of adoption and assignment of texts since the dimensions of text difficulty are generally in line with a common metric that is grade level (McNamara et al., 2014).

However, unidimensional representations of comprehension (unidimensional measures or traditional readability formulas) happen to be ineffective for a number of reasons. First, they have tendency to overlook the importance of readers' deeper levels of understanding. Likewise, traditional readability measures focus on superficial characteristics of text related to readers' understanding of the words and of individual sentences in the text. In other words, they can merely provide robust predictors of sentence-level understanding and the amount of time it takes to read a passage. Second, unidimensional measures don't take into consideration the multiple factors that influence readers' use of knowledge and deep comprehension such as cohesion and text genre. Third, traditional readability formulas are not informative to educators when they need specific guidance for diagnosing a student's uncommon deficit and planning corrective intervention for students (Connor, Morrison, Fishman, Schatschneider, & Underwood, 2007). Moreover, they do not determine text particular characteristics that are likely to challenge a student. They are also not informative enough to teachers on the essential aspects of a text's complexity. Furthermore, it is important to note that while a grade level estimate may tell a teacher that a text is more or less difficult, the difficulty score presents no information on why it is so. It is the multilevel analysis of language and discourse that enables providing such information (McNamara et al., 2014).

On the other hand, as McNamara (2014) put, an analysis of multiple levels of language and discourse, i.e. the multidimensional approach, is potentially beneficial to the scaling and selection of texts. Coh-Metrix is helpful in that it is able to inform the kind of activities and questions teachers might use as they present texts to the class or small groups. Prior knowledge of the potential difficulties of any text enables teachers to create tasks or questions that help students recognize and overcome these difficulties, i.e. an awareness raising strategy.

Tentative comparison between ESP input text and upper grade level 6 science text

Figure 3 is the visualization of differences in easability percentile scores between the ESP input text and some science text adopted for upper grade level 6. The five main Coh-Metrixeasability scores make it possible. Although both texts seem to belong to almost the same genres, there are differences in the easability scores. Figure 3 verifies that ESP text is lower in word concreteness. It presumably means that ESP text includes more abstract concepts than grade level 6 science text, hence more informational. The figure also shows that sentences within the science text contain fewer words and use simpler, familiar syntactic structures that ESP text, hence less challenging to process. As to referential cohesion, ESP text is a text of low-cohesion that is more difficult to process since there are fewer connections that tie the ideas together for the reader. Also, ESP text is distinctively rich in deep cohesion. It means that it includes more intentional and causal connectives suggesting more logical and causal relationships within it. Such connectives enable the reader to form a more coherent and deeper understanding of the causal actions, processes, and events in the text. Lack of these connectives makes the reader infer the relationships between the ideas within the text. On the other hand, both seem to have great density of information, hence low narrativity. It means that they can leave the reader unscaffolded by his/her prior domain knowledge.

The answers to the research questions

Apart from discussion of the Coh-metrixeasability components and readability measure and tentative comparison of the intended ESP text and grade level 6 science text in terms of easability scores, the current study sought answers to its questions as follows.

1. What is it that enables the target learners to achieve multidimensional mental representation of the text?

To answer the first question, the current study drew on what distinguishes L2 Readability (RDL2) from other two readability formulas—that it not only takes text challenges at the sentence and the word level into consideration, but it also considers the cohesion between sentences in the text—and research findings of the Crossley et al. (2011), Crossley et al. (2008), Dufty et al. (2006), Dufty et al. (2006), and McNamara, Graesser, and Louwerse (2012). Accordingly, these are explicit cohesive characteristics of texts that enable the achievement of multidimensional mental representation of the text on the part of the target learners. In other words, learners' mental representation of the text is not gained unless the text is coherent and coherence of the text is not established unless the text is cohesive enough. Therefore, cohesive characteristics are necessary though not sufficient. Computational linguistics has contributed to the development of software tools (e.g. Coh-Metrix) capable of computing cohesion density of texts. They help teachers and materials writers take care of this issue.

2. How could the target learners be able to achieve multidimensional mental representation of the text?

It is the selection and provision of a text cohesive enough using some objective metrics. Exposure to such texts is likely to make learners able to achieve multidimensional mental representation of the text.

Conclusion

Core text selection as one of the most important stages in the text-driven approach to materials development urgently requires some more objective indices or metrics. The guidelines stated by Tomlinson and Masuhara (2018) are not self-adequate: they allow merely for subjective, intuitive, impressionistic evaluation and scaling of texts though it is systematically carried out on a 5-point scale and excludes any text that fails to achieve at least 4 on each of the criteria above. Moreover, these rubrics might not work at all for the non-natives, less experienced teachers and materials writers because, as McNamara et al. (2014) put, even the publisher-assigned grade level of texts assumedly derived from the intuition of expert judgment in addition to other sources of information. Therefore, the need for more solid, objective ways to evaluate, and in turn, to select the core text is acknowledged.

The most important criterion stated by Tomlinson (2003) is the likelihood of the target learners being able to achieve multidimensional mental representation of the text. Research shows that these are explicit cohesive characteristic of texts that make it happen on the part of the target learners. Therefore, analysis of the cohesive characteristics using some objective metrics is necessary though not sufficient when selecting and scaling the core texts.

To meet this requirement there may be many linguistic computational tools. Coh-Metrix is one that provides teachers and material developers with such objective indices. In its public version, it generates about 106 indices of which six ones are the principal predictors of the text complexity: word concreteness, syntactic simplicity, referential cohesion, causal cohesion, narrativity, Coh-Metrix L2 readability. The first five are evidentially found to be the main factors that account for most of the variance in texts across grade levels and text categories/genres. Coh-Metrix indices of cohesion (individually and combined) significantly distinguished the high- versus low-cohesion versions of texts (McNamara et al., 2010). It is worth noting that the first five, aka text easability principal components, augment Coh-Metrix L2 readability formula by providing a picture of the sources of challenges within texts. L2R, the last one, is capable of specifically predicting the readability of texts for second language readers: the commonly used readability indexes (e.g., Flesch–Kincaid) were inappropriately distinguished between high and low-cohesion texts. These measures put together can help teachers and materials developers select and grade the core texts more objectively so that the transition from one grade to another gets safe and secure.

This study made use of Coh-Metrix public web application to analyze Unit 8 main text from the textbook English for Computer Engineering. Output cohesion indices of the sample ESP text were compared with some grade level 6 science text. The comparison was made to find how smooth the transition from General English to English for Specific Purposes happens. Are GE texts narrative enough? Or are ESP texts informational enough? How is a safe and smooth transition from GE to ESP guaranteed? The construct of narrativity is not dichotomous. In other words, it is a matter of degree. The more narrative a text is, the less informational it is, and vice versa. Secure transition from GE to ESP requires some text capable of bridging the gap in between, of hybrid nature trading off some narrativity for being a little more informational, a text this is, metaphorically speaking, science fiction containing not only characters, events and actions but also objects and ideas.

Finally, it concluded that explicit cohesive characteristics of texts will enable the achievement of multidimensional mental representation of the text if it is selected and assigned to the readers by means of some objective metrics. It implies that this enabling potential can be realized by Iranian EFL teachers and materials developers as they are evaluating and selecting core texts.

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Appendices

Appendix A

Yousefkhani, M., Ayat, N., &Farrahi, A. (1385). English for Computer Engineering. Tehran: Payam Noor Universirty Press.

Unit 8 (pp 63-64)

Application Service Providers

If your hard disk is packed to bursting point, the IT department is far too busy to fix your email problems and your business can't afford to buy the tools that you'd like to develop the company website, then its time to think about using an application service provider (ASP). Rather than installing software on each machine or server within your organization, you rent applications from the ASP, which provides remote access to the software and manages the hardware required to run the applications.

There are a lot of advantages to this approach. The havoc caused by viruses makes the idea of outsourcing your email and office suite services an attractive option. It also gives you more flexibility—you pay for applications as and when you need them, rather than investing in a lot of costly software which you're then tied to for years. Not having to worry about upgrading to the latest version of your office suite or about battling with the complexities of managing an email system, leaves businesses with more time. Time to focus on what they do best.

However, there are some potential pitfalls. To use applications remotely requires a lot of bandwidth, which is only really available from a broadband connection or a leased line to the ASP itself. It is also important to ensure that the ASP will be able to provide a secure, reliable service which will be available whenever you need it.

Providing applications and storage space for vast numbers of users requires some powerful technology on the part of the ASP. This includes security controls and data storage as well as providing the physical links to customers. For the most part, ASPs don't own the data centers that store the information. Instead, they lease space from data storage specialists. In this way, they can be confident of meeting customers' increasing storage requirements by buying more space as it's needed.

There's a wide variety of applications available for use via ASPs. Office suite applications and email services are two of the most generic applications available through ASPs. Large, complex business applications such as enterprise resource planning tools like SAP are another candidate for delivery through an ASP. Other business services, such as payroll and accounting systems are also available. This is particularly beneficial to small businesses which are likely to grow quickly and don't want to deal with the problems caused by outgrowing their existing system and having to move to a high-end package. ASPs also offer a means of using specialist tools that would otherwise prove prohibitively expensive. Small businesses have the opportunity to use such tools for short periods of time as and when they need them, rather than having to buy the software as a permanent investment.

One of the major barriers for small businesses which want to make a start in e-commerce is ensuring that they have sufficient resources to cope with sudden large increases in customers. This means not only having adequate storage for all your customers' details, but ensuring that you have the technology in place to handle stock levels, efficient delivery and large volumes of traffic. It's very rare for an e-commerce business to handle all of these elements by itself, making this one of the best-established areas of ASP use. Being able to respond rapidly to changes in the size of your customer base and the type of product that they want to order from your business, demands more flexibility than traditional software can provide.

Appendix B

The Coh-Metrix Full Result Table (3 pages)

Number	Label	Label V2.x	Text	Full description
Descriptive				
1	DESPC	READNP	6	Paragraph count, number of paragraphs
2	DESSC	READNS	28	Sentence count, number of sentences
3	DESWC	READNW	590	Word count, number of words
4	DESPL	READAPL	4.667	Paragraph length, number of sentences in a paragraph, mean
5	DESPLd	n/a	1.862	Paragraph length, number of sentences in a pragraph, standard deviation
6	DESSL	READASL	21.071	Sentence length, number of words, mean
7	DESSLd	n/a	11.160	Sentence length, number of words, standard deviation
8	DESWLsy	READASW	1.614	Word length, number of syllables, mean
9	DESWLsyd	n/a	0.940	Word length, number of syllables, standard deviation
10	DESWLlt	n/a	4.885	Word length, number of letters, mean
11	DESWLltd	n/a	2.710	Word length, number of letters, standard deviation

Text Easability Principle Component Scores				
12	PCNARz	n/a	-0.391	Text Easability PC Narrativity, z score
13	PCNARp	n/a	34.830	Text Easability PC Narrativity, percentile
14	PCSYNz	n/a	-0.308	Text Easability PC Syntactic simplicity, z score
15	PCSYNp	n/a	38.210	Text Easability PC Syntactic simplicity, percentile
16	PCCNCz	n/a	-0.782	Text Easability PC Word concreteness, z score
17	PCCNCp	n/a	21.770	Text Easability PC Word concreteness, percentile
18	PCREFz	n/a	-0.658	Text Easability PC Referential cohesion, z score
19	PCREFp	n/a	25.780	Text Easability PC Referential cohesion, percentile
20	PCDCz	n/a	1.581	Text Easability PC Deep cohesion, z score
21	PCDCp	n/a	94.290	Text Easability PC Deep cohesion, percentile
22	PCVERBz	n/a	-0.703	Text Easability PC Verb cohesion, z score
23	PCVERBp	n/a	24.200	Text Easability PC Verb cohesion, percentile
24	PCCONNz	n/a	-2.318	Text Easability PC Connectivity, z score
25	PCCONNp	n/a	1.040	Text Easability PC Connectivity, percentile
26	PCTEMPz	n/a	1.146	Text Easability PC Temporality, z score
27	PCTEMPp	n/a	87.290	Text Easability PC Temporality, percentile

Referential Cohesion				
28	CRFNO1	CRFBN1um	0.556	Noun overlap, adjacent sentences, binary, mean
29	CRFAO1	CRFBA1um	0.630	Argument overlap, adjacent sentences, binary, mean
30	CRFSO1	CRFBS1um	0.593	Stem overlap, adjacent sentences, binary, mean
31	CRFNOa	CRFBNaum	0.284	Noun overlap, all sentences, binary, mean
32	CRFAOa	CRFBAaum	0.436	Argument overlap, all sentences, binary, mean
33	CRFSOa	CRFBSaum	0.409	Stem overlap, all sentences, binary, mean
34	CRFCWO1	CRFPC1um	0.098	Content word overlap, adjacent sentences, proportional, mean
35	CRFCWO1d	n/a	0.106	Content word overlap, adjacent sentences, proportional, standard deviation
36	CRFCWOa	CRFPCaum	0.058	Content word overlap, all sentences, proportional, mean
37	CRFCWOad	n/a	0.081	Content word overlap, all sentences, proportional, standard deviation

LSA				
38	LSASS1	LSAassa	0.209	LSA overlap, adjacent sentences, mean
39	LSASS1d	LSAassd	0.157	LSA overlap, adjacent sentences, standard deviation
40	LSASSp	LSApssa	0.195	LSA overlap, all sentences in paragraph, mean
41	LSASSpd	LSApssd	0.131	LSA overlap, all sentences in paragraph, standard deviation
42	LSAPP1	LSAppa	0.385	LSA overlap, adjacent paragraphs, mean
43	LSAPP1d	LSAppd	0.106	LSA overlap, adjacent paragraphs, standard deviation
44	LSAGN	LSAGN	0.308	LSA given/new, sentences, mean
45	LSAGNd	n/a	0.103	LSA given/new, sentences, standard deviation

Lexical Diversity				
46	LDTTRc	TYPTOKc	0.683	Lexical diversity, type-token ratio, content word lemmas
47	LDTTRa	n/a	0.458	Lexical diversity, type-token ratio, all words
48	LDMTLD	LEXDIVTD	110.611	Lexical diversity, MTLD, all words
49	LDVOCD	LEXDIVVD	106.417	Lexical diversity, VOCD, all words
Connectives				
50	CNCAll	CONi	103.390	All connectives incidence
51	CNCCaus	CONCAUSi	38.983	Causal connectives incidence
52	CNCLogic	CONLOGi	50.847	Logical connectives incidence
53	CNCADC	CONADVCONi	22.034	Adversative and contrastive connectives incidence
54	CNCTemp	CONTEMPi	22.034	Temporal connectives incidence
55	CNCTempx	CONTEMPEXi	18.644	Expanded temporal connectives incidence
56	CNCAdd	CONADDi	49.153	Additive connectives incidence
57	CNCPos	n/a	0	Positive connectives incidence
58	CNCNeg	n/a	0	Negative connectives incidence

Situation Model				
59	SMCAUSv	CAUSV	20.339	Causal verb incidence
60	SMCAUSvp	CAUSVP	30.508	Causal verbs and causal particles incidence
61	SMINTEp	INTEi	13.559	Intentional verbs incidence
62	SMCAUSr	CAUSC	0.462	Ratio of casual particles to causal verbs
63	SMINTEr	INTEC	2.222	Ratio of intentional particles to intentional verbs
64	SMCAUSlsa	CAUSLSA	0.074	LSA verb overlap
65	SMCAUSwn	CAUSWN	0.413	WordNet verb overlap
66	SMTEMP	TEMPta	0.963	Temporal cohesion, tense and aspect repetition, mean
Syntactic Complexity				
67	SYNLE	SYNLE	6.25	Left embeddedness, words before main verb, mean
68	SYNNP	SYNNP	0.966	Number of modifiers per noun phrase, mean
69	SYNMEDpos	MEDwtm	0.663	Minimal Edit Distance, part of speech
70	SYNMEDwrd	MEDawm	0.896	Minimal Edit Distance, all words
71	SYNMEDlem	MEDalm	0.882	Minimal Edit Distance, lemmas
72	SYNSTRUTa	STRUTa	0.122	Sentence syntax similarity, adjacent sentences, mean
73	SYNSTRUTt	STRUTt	0.087	Sentence syntax similarity, all combinations, across paragraphs, mean

Syntactic Pattern Density				
74	DRNP	n/a	364.407	Noun phrase density, incidence
75	DRVP	n/a	216.949	Verb phrase density, incidence
76	DRAP	n/a	25.424	Adverbial phrase density, incidence
77	DRPP	n/a	132.203	Preposition phrase density, incidence
78	DRPVAL	AGLSPSVi	0	Agentless passive voice density, incidence
79	DRNEG	DENNEGi	5.085	Negation density, incidence
80	DRGERUND	GERUNDi	33.898	Gerund density, incidence
81	DRINF	INFi	35.593	Infinitive density, incidence

Word Information				
82	WRDNOUN	NOUNi	267.796	Noun incidence
83	WRDVERB	VERBi	123.729	Verb incidence
84	WRDADJ	ADJi	94.916	Adjective incidence
85	WRDADV	ADVi	50.848	Adverb incidence
86	WRDPRO	DENPRPi	59.322	Pronoun incidence
87	WRDPRP1s	n/a	0	First person singular pronoun incidence
88	WRDPRP1p	n/a	0	First person plural pronoun incidence
89	WRDPRP2	PRO2i	28.814	Second person pronoun incidence
90	WRDPRP3s	n/a	0	Third person singular pronoun incidence
91	WRDPRP3p	n/a	15.254	Third person plural pronoun incidence
92	WRDFRQc	FRCLacwm	2.186	CELEX word frequency for content words, mean
93	WRDFRQa	FRCLaewm	2.910	CELEX Log frequency for all words, mean
94	WRDFRQmc	FRCLmcsm	1.052	CELEX Log minimum frequency for content words, mean
95	WRDAOAc	WRDAacwm	404.294	Age of acquisition for content words, mean
96	WRDFAMc	WRDFacwm	563.856	Familiarity for content words, mean
97	WRDCNCc	WRDCacwm	352.201	Concreteness for content words, mean
98	WRDIMGc	WRDIacwm	379.200	Imagability for content words, mean
99	WRDMEAc	WRDMacwm	408.435	Meaningfulness, Colorado norms, content words, mean
100	WRDPOLc	POLm	3.841	Polysemy for content words, mean
101	WRDHYPn	HYNOUNaw	7.562	Hypernymy for nouns, mean
102	WRDHYPv	HYVERBaw	1.632	Hypernymy for verbs, mean
103	WRDHYPnv	HYPm	2.163	Hypernymy for nouns and verbs, mean

Readbility				
104	RDFRE	READFRE	48.904	Flesch Reading Ease
105	RDFKGL	READFKGL	11.673	Flesch-Kincaid Grade level
106	RDL2	L2	16.098	Coh-Metrix L2 Readability