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A Reading Comprehension Formula of Reader and Text Characteristics

Jaan Mikk and Jaanus Elts
University of Tartu, Estonia

ABSTRACT

Readability formulae predict reading outcomes relying on text characteristics but they do not consider reader abilities. This paper describes ways of formulating a reading comprehension formula which includes reader and text characteristics. An experiment embracing 124 subjects and 48 texts serves to demonstrate the mechanisms through which the formula is developed. The applicability of the formula, its degree of precision, and power of predictability are discussed.

Many text characteristics influence its effectiveness and thorough investigations of these characteristics enable us to predict reading outcomes. Readability formulae have been widely used for that purpose in reading studies in a number of countries. The formulae have recommended themselves as rapid and reliable tools in assessing textbook comprehension (Gray & Leary, 1935; Chall, 1958; Klare, 1963, 1974–1975; Chall & Conard, 1991; Davison & Green, 1988; Zakaluk & Samuels, 1988). Readability formulae for languages other than English are also available, e.g., German (Bamberger & Vanecek, 1984; Tuldava, 1993), Russian (Machkovskii, 1976; Elts, 1992; Kukemelk & Mikk, 1993), Estonian (Mikk, 1991) and others (Klare, 1984). The importance of texts being of appropriate difficulty level for the expected readers has been emphasised by the suggestion that all popular publications should undergo a quality trial through readability assessment (Bruce & Rubin, 1988). Newspaper publishers know very well how important it is for a successful newspaper to be easily readable (Björnsson, 1983).

A new trend has rapidly been developing during the past decades. Computer programs are written to measure text readability (Eglowstein, 1981; Schuyler, 1982; Standal, 1987) and they are often part of editing programs. This means that readability indices can be calculated as soon as the text has been entered into the computer. Complicated linguistic structures are found and simple words or phrases are suggested that can be used to replace the difficult ones. Such programs are of great help to writers and editors of texts (Schalow & Mears, 1986; Wampler et al., 1988-1990).

However the readability formulae have also been subjected to criticism. The criticism levied against reading formulae is often directed against poor results due to the wrong application of the formulae on the one hand, and against these formulae that indeed need improvement on the other hand. The improvement should take account of new quantitative text characteristics developed in quantitative linguistics.

Our new approach to readability formula formation is meant to overcome one of the weaknesses of readability formulae. Namely, it has been repeatedly reported that reading comprehension is apt to vary significantly depending on the reader’s motivation (Bruce & Rubin, 1988, p. 8), interest and previous knowledge of the subject matter (Baker et al., 1988; Entin & Klare, 1985), or reading skills and habits. Consequently, the characteristics should be included in readability formula (Anderson & Davison, 1989).

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The present article offers a technique resulting in new reading comprehension formulae using the characteristics of the text and the reader. The technique is demonstrated on an experimental investigation.

METHOD

Basic Principles
Many readability formulae referred to in the literature are based on the data provided by McCall-Grabb’s reading test. The test scores are taken to indicate the difficulty levels of the texts tested. The textual characteristics include the sentence length, the word length, the percentage of oversized words, and so on. The test scores and the textual characteristics are presented in a tabulated form, each line of the table representing one text (Table 1). The readability formula is arrived at through regression analysis of the experimental data.

Table 1 presents the mean scores for a sample of subjects. The table does not contain the scores for each subject, and therefore the data are too generalised to represent indices of the abilities of the individuals. To formulate a more precise formula more specific initial data are required. Besides text characteristics, the table of the initial data should also include reader characteristics (Table 2). Each line in Table 2 represents a description of the comprehension of a text in the experiment by one of the experimental subjects. It therefore comprises text characteristics, reader characteristics and the comprehension level achieved. Both subgroups of characteristics should be subjected to regression analysis and included in the new readability formula.

Some readability formulae have not been developed through experiments. Usually the numerical coefficients in these formulae have been expressed by whole numbers. As there is no experimental basis, there is no external validity evaluation and the results have unknown predictive value.

Description of the Experiment
Our study is based on the analysis of forty-eight biology texts chosen from popular science books published in Russian. To have a greater variety of texts, only one or two texts were taken from each book, the interval between the two samples being twenty pages. There were no illustrations or formulae in the texts.

The difficulty of the texts was assessed by 124 students in Grades 7, 8 & 10, aged 14–17 years, in two Russian schools in Estonia. The test was conducted by the teachers of biology in those schools. The teachers had been instructed in the methodology of the experiment.

Open-ended answers constituted the response mode required for the 8 to 10 questions prepared to cover the information contained in each text passage. The number of questions in the set had to be limited to ten, because otherwise some of the questions would have contained answers to some other questions in the set. On the other hand, the 257-word text contained more information than could be represented by ten questions, so four versions of question sets, eight to ten questions each, were drawn up.

Table 1. Indices used in readability formula formulation. (Example)

<table>
<thead>
<tr>
<th>No.</th>
<th>Heading of the text</th>
<th>Difficulty of the text</th>
<th>Characteristics of the text</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Sentence length</td>
</tr>
<tr>
<td>1.</td>
<td>Cat</td>
<td>30</td>
<td>17</td>
</tr>
<tr>
<td>2.</td>
<td>Evolution</td>
<td>70</td>
<td>24</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The experiment was carried out with every text at a lesson as follows. First, to measure the students’ knowledge of the subject matter they were asked to take a test on answering questions before they were given the text. The test was one of the versions of free-response questions composed on the text that would be studied in this lesson. Testees were not allowed to find answers in their biology textbooks, ask for the teacher’s help, or speak with other students during the whole experiment. Deskmates had texts and questions of different content. Second, after the preparatory test was done and collected, the cloze test was done and collected. Third, testees were given the whole text to study for 15–20 minutes. The students were asked to read and learn the text by themselves. Fourth, the texts were collected and the teacher gave the students a new version of the free-response test. So the students’ achievements were measured by different tests before and after each text was studied. Fifth and finally, a questionnaire was filled in. Students wrote how difficult and interesting the text was, if the information was familiar before they read the text, and so on. The questionnaire had two-point scales. For example, 1 – uninteresting, 2 – interesting. The percentage of the correct answers for each text was calculated. An answer was considered correct if the essential information it contains was correct. The inter-scorer reliability in our experiment was 0.91.

Student abilities must also be measured, as they undeniably affect the outcome of information acquisition. As there are no generally accepted ability tests for Russian students, we took the mean score of each student to represent the index of the reading ability of that particular student.

The aim of the text analysis was to find text characteristics that might influence learning effectiveness. In general 242 characteristics of texts under study were established. The characteristics may be grouped as follows.

1. Knowledge of the vocabulary: texts that are characterised by a large number of unknown words associate poorly with students’ experience and are difficult to understand. We used the frequency count of Russian speech and the following scale of terminologicality:
   a. everyday nouns that are not professional terms (e.g., plant, winter);
   b. professional terms of everyday meaning (e.g., eyelid, blue anemone);
   c. professional terms that are not used in everyday speech (e.g., replication, DNA).

   

The abstractness of the matter described in the text: more abstract texts assume higher levels of abstract thinking and cause more difficulties in comprehension of the text. We used the following scale of abstractness:
   a. concrete nouns designating things directly perceivable by senses (e.g., man, stone);
   b. nouns designating phenomena and processes perceivable by senses (e.g., rain, light);
   c. abstract noun designating objects and notions imperceivable directly by senses (e.g., evolution, cell).

<table>
<thead>
<tr>
<th>No.</th>
<th>Subjects</th>
<th>Characteristics of the subjects</th>
<th>Text’s characteristics</th>
<th>Level of comprehension</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Reading ability</td>
<td>Reading time</td>
<td>Sentence length</td>
</tr>
<tr>
<td>1.</td>
<td>Mary</td>
<td>90</td>
<td>7</td>
<td>15</td>
</tr>
<tr>
<td>2.</td>
<td>Mary</td>
<td>90</td>
<td>6</td>
<td>18</td>
</tr>
<tr>
<td>3.</td>
<td>Tom</td>
<td>83</td>
<td>8</td>
<td>18</td>
</tr>
</tbody>
</table>

Table 2. Data for elaborating reading comprehension formula (Example).
3. The word length: long words are usually more difficult to understand.
4. The sentence length: linking its parts may make long sentences difficult and contribute to fragmentary understanding of the sentences. We used mean sentence length and percentage of sentences exceeding optimal value.

All the texts were computer-analysed. They were subjected to morphological analysis with the help of the programs worked out in Kiev by N.P. Dartschuk and her colleagues (Automation…, 1984). The frequency rating of every word in the texts plotted against the computerised frequency list of Russian speech was found by T. Tamman. The frequency list of words of Russian speech was elaborated at Moscow University by D.A. Buchstab and her colleagues.

We grouped the experimental data into two sets. The first set (Table 1) included the mean values of text difficulty assessments for 48 texts and the formal textual characteristics, so this set can be referred to as the set of textual indices. The second set (Table 2) included the test scores of each student on each text and also the textual characteristics and characteristics of students, so we refer to this set of characteristics as the set of the learner. The mathematical means, standard deviations, correlation indices, and regression lines were calculated for each of the sets.

RESULTS

Some of the characteristics, their average values, and standard deviations are given in Table 3. Standard deviations are given for the set of the learner. In the set of the textual characteristics the standard deviations for indices of text effectiveness (numbers 23–28) were 2-3 times smaller because the set contained mean values of textual effectiveness indices.

Among the six indices of reading effectiveness (no 23–28) the post-test score (Number 28) had the best intercorrelations. The next two best indices were cloze test results (Number 27) and interestingness rating (Number 23). The three best indices of reading effectiveness were included in the factor analysis. The results of the analysis are presented in Table 4. We see in the table that the most valid index of reading effectiveness was the final test score. Therefore we elaborate comprehension prediction formulae for the final test score.

Correlations between the final test score and textual characteristics are given in Table 3 for both sets of data. We see in the table that correlations are higher in the set of textual characteristics while mean values of the characteristics are more reliable than results of individual measurement.

Applying regression analysis to our data we elaborated comprehension prediction formulae. The formula for the set of textual characteristics was as follows:

\[
FT = 116 - 0.262 \cdot X_3 - 0.74 \cdot X_7 - 9.88 \cdot X_{18} - 15.0 \cdot X_{19}
\]

where:
- \(FT\) – results of final test in per cent,
- \(X_3\) – percentage of sentences of 70 or more letter spaces,
- \(X_7\) – percentage of words of 9 or more letters,
- \(X_{18}\) – mean abstractness of nouns,
- \(X_{19}\) – mean terminological index of nouns.

The coefficient of multiple correlation was 0.86 and the standard error of the estimate was 8.2. All coefficients are significant at the 0.05 level.

The formula for the set of the learners was as follows:

\[
FT = 81.7 - 0.987 \cdot X_1 - 0.29 \cdot X_3 - 0.702 \cdot X_7 - 9.47 \cdot X_{18} - 15.2 \cdot X_{19}
\]

where \(X_1\) stands for abilities of testees and the other symbols are the same as in Formula (1). The coefficient of multiple correlation was 0.71 and the standard error of the estimate was 22. All the coefficients were significant at the 0.01 level.
Table 3. List of text characteristics and their correlation coefficients with final test score.

<table>
<thead>
<tr>
<th>No.</th>
<th>Name of the characteristic</th>
<th>Average</th>
<th>Standard deviation</th>
<th>Correlation with final test score in the set of the learner (df = 4273)</th>
<th>Correlation with final test score in the set of text characteristics (df = 46)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Abilities of testees</td>
<td>38</td>
<td>17</td>
<td>.54</td>
<td>.52</td>
</tr>
<tr>
<td>2</td>
<td>Percentage of sentences of 4 or more words</td>
<td>97</td>
<td>5</td>
<td>-.29</td>
<td>-.52</td>
</tr>
<tr>
<td>3</td>
<td>Percentage of sentences of 70 or more letter spaces</td>
<td>76</td>
<td>20</td>
<td>-.41</td>
<td>-.75</td>
</tr>
<tr>
<td>4</td>
<td>Percentage of sentences of 80 or more letter spaces</td>
<td>68</td>
<td>23</td>
<td>-.41</td>
<td>-.74</td>
</tr>
<tr>
<td>5</td>
<td>Percentage of sentences of 110 or more letter spaces</td>
<td>48</td>
<td>25</td>
<td>-.38</td>
<td>-.69</td>
</tr>
<tr>
<td>6</td>
<td>Percentage of sentences of 190 or more letter spaces</td>
<td>13</td>
<td>14</td>
<td>-.29</td>
<td>-.51</td>
</tr>
<tr>
<td>7</td>
<td>Percentage of words of 9 or more letters</td>
<td>26</td>
<td>7</td>
<td>-.42</td>
<td>-.78</td>
</tr>
<tr>
<td>8</td>
<td>Percentage of words of 10 or more letters</td>
<td>19</td>
<td>6</td>
<td>-.42</td>
<td>-.78</td>
</tr>
<tr>
<td>9</td>
<td>Mean number of letters in a word</td>
<td>6.3</td>
<td>0.6</td>
<td>-.41</td>
<td>-.76</td>
</tr>
<tr>
<td>10</td>
<td>Modification ratio (Wiio, 1968)</td>
<td>0.44</td>
<td>0.09</td>
<td>.17</td>
<td>.29</td>
</tr>
<tr>
<td>11</td>
<td>Percentage of words with the frequency index lower than 30 in spoken language</td>
<td>63</td>
<td>5</td>
<td>-.35</td>
<td>-.65</td>
</tr>
<tr>
<td>12</td>
<td>Mean frequency of textual nouns in spoken language</td>
<td>27</td>
<td>17</td>
<td>.26</td>
<td>.48</td>
</tr>
<tr>
<td>13</td>
<td>Mean substantival frequency in a text</td>
<td>1.3</td>
<td>0.1</td>
<td>-.26</td>
<td>-.47</td>
</tr>
<tr>
<td>14</td>
<td>Percentage of nouns with frequency of occurrence lower than 30 in the spoken language</td>
<td>85</td>
<td>7</td>
<td>-.26</td>
<td>-.49</td>
</tr>
<tr>
<td>15</td>
<td>Mean verbal frequency in a text</td>
<td>1.2</td>
<td>0.1</td>
<td>.03</td>
<td>.04</td>
</tr>
<tr>
<td>16</td>
<td>Percentage of verbs not included in spoken language</td>
<td>22</td>
<td>10</td>
<td>.14</td>
<td>.24</td>
</tr>
<tr>
<td>17</td>
<td>Percentage of verbs with frequency lower than 30 in spoken language</td>
<td>68</td>
<td>12</td>
<td>.02</td>
<td>.02</td>
</tr>
<tr>
<td>18</td>
<td>Mean abstractness of nouns</td>
<td>1.8</td>
<td>0.3</td>
<td>-.36</td>
<td>-.66</td>
</tr>
<tr>
<td>19</td>
<td>Mean terminological index of nouns</td>
<td>1.5</td>
<td>0.2</td>
<td>-.30</td>
<td>-.56</td>
</tr>
<tr>
<td>20</td>
<td>Percentage of nouns of medium abstractness</td>
<td>28</td>
<td>11</td>
<td>.05</td>
<td>.10</td>
</tr>
<tr>
<td>21</td>
<td>Percentage of abstract nouns</td>
<td>23</td>
<td>16</td>
<td>-.38</td>
<td>-.71</td>
</tr>
<tr>
<td>22</td>
<td>Percentage of terms</td>
<td>13</td>
<td>11</td>
<td>-.34</td>
<td>-.64</td>
</tr>
<tr>
<td>23</td>
<td>Level of interest evoked by a text</td>
<td>1.5</td>
<td>0.5</td>
<td>.46</td>
<td>.93</td>
</tr>
<tr>
<td>24</td>
<td>Familiarity of texts</td>
<td>1.1</td>
<td>0.3</td>
<td>.15</td>
<td>.64</td>
</tr>
<tr>
<td>25</td>
<td>Sufficiency of time</td>
<td>1.7</td>
<td>0.5</td>
<td>.21</td>
<td>.70</td>
</tr>
<tr>
<td>26</td>
<td>Level of prior knowledge (in percent)</td>
<td>5.7</td>
<td>11.7</td>
<td>.34</td>
<td>.72</td>
</tr>
<tr>
<td>27</td>
<td>Cloze test score (in percent)</td>
<td>32</td>
<td>22</td>
<td>.58</td>
<td>.90</td>
</tr>
<tr>
<td>28</td>
<td>Final test score (in percent)</td>
<td>38</td>
<td>31</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4. Factor loadings of the indices of reading effectiveness.

<table>
<thead>
<tr>
<th>No.</th>
<th>Indice</th>
<th>Factor loading in the set of textual characteristics</th>
<th>Factor loading in the set of the learner</th>
</tr>
</thead>
<tbody>
<tr>
<td>23</td>
<td>Level of interest</td>
<td>0.97</td>
<td>0.73</td>
</tr>
<tr>
<td>27</td>
<td>Cloze test score</td>
<td>0.96</td>
<td>0.81</td>
</tr>
<tr>
<td>28</td>
<td>Final test score</td>
<td>0.97</td>
<td>0.86</td>
</tr>
</tbody>
</table>
DISCUSSION

Five groups of text characteristics have correlation values over 0.6 with the results of the final test in the set of textual characteristics: percentage of long sentences (Number 3: $r = -0.75$), percentage of long words (Number 7: $r = -0.78$), percentage of rare words (Number 11: $r = -0.65$), percentage of abstract nouns (Number 21: $r = -0.71$), and percentage of terms (Number 22: $r = -0.64$) (Table 3). Readability Formula (1) contains characteristics from all the groups except one. The percentage of rare words in the text was not included in the formula as it correlates well (over 0.6) with sentence length and word length.

Formula (1) includes two arguments seldom used in readability formulae: the mean abstractness of nouns and their mean terminological index.

It has been demonstrated in many investigations that texts containing many abstract words are difficult to understand (Begg & Paivio, 1969; Flesch, 1950; Klare, 1974-1975; Kübarsepp & Mikk, 1993; Tschistjakova, 1975). The reader can visualise concrete nouns which contributes to better understanding. S. Kemper (1988) has recently developed an inference load formula in which the density of mental states is an important argument of text complexity. It correlates with the idea of abstractness as a fundamental factor of textual difficulty. The value of text abstractness can be easily computerised if the abstractness value of every noun has been entered into the computer dictionary.

The second new argument in the readability Formula (1) concerns terms in texts. Terms tend to be unknown to students and they cause difficulties in understanding the text. Many textbooks in Europe and America hold too many terms. Some textbooks are known to contain 1000–2000 terms (Merzyn, 1987a). One third of the terms in one textbook are different from the terms in another textbook for the same grade and subject (Merzyn, 1987). There are too many names and events in history textbooks (Mehlinger, 1989). Indices of term density are an important argument in new readability formulae.

Formula (1) in our example helps to predict comprehension test scores for Russian 8th graders reading popular scientific biological texts. It is a traditional readability formula, but it is more precise because its arguments are per cent expressions of oversized words and oversized sentences, whereas in traditional formulae these arguments are given in mean values (Elts & Mikk, 1996). We think that it is more precise and informative to predict the test score of a particular student after reading a text than it is to predict the suitability of a particular text for a certain grade level of students.

Besides textual characteristics Formula (2) also includes reader characteristics. So far reading formulae have mostly been aimed at measuring textual characteristics and assessing textual complexity. Reader abilities were measured using other techniques. To assess the suitability of a text for a reader the two scores were matched. Formula (2) described in this paper makes it possible to carry out textual readability assessment for a certain reader.

Although the paper is mostly devoted to theoretical questions of formula formation, the proposed formulae are also of practical value. All the predictor variables in Formula (1) can be calculated by computer if the computer dictionary includes abstractness and terminologicality indices of nouns. The use of Formula (2) calls for the reading ability of the reader to be measured besides the textual characteristics. In our experiment Texts Numbers 9, 16, 19, 22, 33, 46, and 47 proved to be best suited for measurement, because their scores were closest to the mean value of reader ability. The reliability of the mean test score of these seven texts was 0.9.

Standardized reading tests can be used to assess reader characteristics for formulae like Formula (2). However, one should remember that the procedures for measuring reader abilities should be the same for formula development and for formula application.

All comprehension levels (50%, 75%, or 100%) have been considered appropriate in the relevant literature (Bormuth, 1968; Klare, 1988). Usually the 75% level is preferred, but the appropriate level of comprehension depends very much on the conditions and objectives of
the reading process. The expected comprehension level in Formula (2) is expressed in percent, which makes it easy for the teacher to decide whether the level meets the requirements set out for the reader. We can say that the formula of the new type has more relevant criteria of optimality assessment than the traditional ones.

In principle, the formula including reader characteristics should be more precise, but in our experiment we could not prove the superiority of Formula (2) over Formula (1). The lower multiple correlation index for Formula (2) in comparison with Formula (1) can be accounted for by the larger measurement errors for Formula (2) due to the test variants being of slightly modified difficulty levels, and also due to the variations in the testing conditions. However, the factors, though reflected in the value of the standard error by formula formulation, are insignificant by formula application and the actual value of the standard error of measurement can be expected to be somewhat lower in the formula application than it was in Formula (2) development. Nevertheless methods of getting more reliable and valid measures of comprehension of a text by a reader are needed. One of the possibilities is to sum up cloze test score and final test score into one index of text comprehension.

As a matter of fact the two formulae should have the same level of precision if a reader and a text are matched. The standard error of matching a text and a reader will compound from the standard error of Formula (1) and the standard error of the reading ability test. The standard error of Formula (2) accounts for the error of both measurements.

The textual characteristics in Formula (1) and Formula (2) are the same and the coefficients are of practically the same value. This could be expected, as textual characteristics influence comprehension in the same way whether measured in individuals or in groups. The new argument in Formula (2) – reader ability – could not influence the coefficients of the textual characteristics because there could be no correlation between the textual characteristics and the reader characteristics.

Formula (2) includes only one learner characteristic. Other characteristics can be included in the reading prediction formula also. Besides additional learner characteristics it will be more precise to vary the boundary line of long words and sentences depending on the reader’s eye span and memory span (Miller & Kintsch, 1980). It can be done easily in the computerized analysis of textual difficulty levels for individual readers. Computerized readability analysis is included in modern text editors (Word Perfect, Word, etc.) and it is possible to elaborate programs that allow the operator to enter additional parameters of individual reading ability, memory span, and others into the program.

CONCLUSION

Many researchers and educationalists have insisted on a readability formulae that would combine text characteristics and reader characteristics. A formula of this kind can be developed on the basis of tabulated values characterising reader abilities, text parameters and an experimentally proved level of text comprehension by the reader. The method of formula formation is regression analysis.

The new formula predicts the comprehensibility level of a text for a reader. Formulae to measure the interest of the text for the reader and other parameters of the outcome of reading can be developed for most texts and languages using the formulation procedure described in this paper. In general, the procedure can be used to formulate predicting methods for a large range of learning outcomes and include the multiplicity of learner and text factors.

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