Text Classification for Children with Dyslexia employing User Modelling Techniques

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***Abstract*—The problem of text-readability has received great attention in the literature. However, the classification of a text as readable is based solely in its linguistic complexity and does not take into account the skills of the intended reader. In this paper, we make a first attempt to study user-specific text readability. We focus on readers with dyslexia and documents written in English and Greek.**

Central to our approach is the notion of the user's profile which carries information regarding the linguistic difficulties a user with dyslexia may experience. Based on the user's profile, we develop heuristics for evaluating text's readability for the specific user. The developed heuristics are incorporated in the text classification services of the iLearnRW[1] project, aiming to facilitate the selection of appropriate/suitable reading resources for children with dyslexia.

I. Introduction

A child that learns to read and/or write will practice with several pieces of text. However, not all text is appropriate to be used in the learning process (either for reading or for writing) of a particular child. The level of difficulty (or "degree of appropriateness") of the text must be carefully considered. For a child without learning difficulties, the degree of appropriateness of a text depends on formal, linguistic factors, the text content as well as the child's age. For children with learning difficulties, these factors need to be considered with respect to each child's special educational needs. In that sense, text classification with respect to particular language difficulties encountered in dyslexia would be a very useful process, enabling teachers to select the appropriate content for a particular learner and formulate a more individualized educational plan. The Text Classification approach described in this paper has been developed in the context of *iLearnRW* (Integrated Intelligent Learning Environment for Reading and Writing), an ongoing European Union funded project.

In this paper, we describe the Text Classification Module (TCM) that is incorporated in the iLearnRW software. The design of the TCM aims to provide individualized teaching assistance to children with dyslexia by enabling a teacher or parent to classify texts with respect to the degree of appropriateness for a particular child, based on his/her profile, as well as to search for appropriate content for a particular child. To this end, the notion of text readability was analysed based on linguistic complexity issues which, to a great extent, determine the suitability of a text for a particular learner.

To the best of our knowledge, it is the first time that personalized (based on user's profile/characteristics) text classification is attempted. Even though in our work we focus on a specific class of users, children with dyslexia, our approach is applicable to the general user.

This paper is organized as follows: In Section II, we describe the basic notions related to linguistic complexity and reading difficulty while, in Section III, we present a brief review of commonly used readability formulas. In Section IV, we describe the developed user models that capture the reading learning process for the English and Greek languages while, in Section V, we present our user-specific text classification methods. Section VI presents an application employing the developed text classification method. Finally, Section VII presents preliminary evaluation results.

II. Linguistic complexity and reading difficulty

Text readability is closely related to and even determined by the linguistic complexity of a text in the sense that the readability of a text increases as linguistic complexity decreases and vice versa. Therefore, linguistic complexity is a central notion when dealing with text classification.

Defining linguistic complexity is currently one of the most hotly debated notions in linguistics. In a first quantitative description of linguistic complexity, Blache [1] identifies the types of constructions that are considered complex and thus difficult to process. She differentiates between local complexity, which refers to structural complexity, difficulty, which involves processing aspects and cognitive load, and global complexity, which refers to the language as a system rather than the complexity of a given realization (see [12] for a similar classification). Of the two levels, local complexity is considered measurable and has drawn considerable attention in the literature. Local complexity therefore includes phonological complexity (e.g. size of phonemic inventory, incidence of marked phonemes, phonotactic restrictions, maximum complexity of consonant clusters), morphological complexity (e.g. extent of allomorphy use and morphophonemic processes), syntactic complexity (e.g. level of clausal embedding and recursion), semantic and lexical complexity (e.g. extensive occurrence of homonymy and polysemy, type/token ratios),

[1]iLearnRW: Integrated Intelligent Learning Environment for Reading and Writing.

pragmatic complexity (e.g. degree of pragmatic inferencing) (see [14] for a review).

A. Linguistic complexity and text complexity

The complexity or the degree of challenge of a particular text is the result of combinations and interactions of a variety of factors. These may include linguistic complexity factors, topic familiarity, word difficulty, sentence length, concreteness of ideas and concepts and others. In a description of text complexity, Lipson and Wixson [10] define a number of factors that affect the readability of a text, which include the number of syllables in the words and the number of words in the sentences, while other linguistic characteristics, such as vocabulary and sentence structure, text organization and the amount of background knowledge that is required of readers are also often taken into account when determining the appropriateness of a text for a particular reader [3]. In a more detailed account of the linguistic factors that affect text readability, Hess and Bigham [7] define these factors as the following: word difficulty and sentence structure, text structure, discourse style (e.g. satire or humor), genre, background knowledge, degree of familiarity with text topic, level of reasoning required, organization and layout of text and text length.

In an extensive review of readability research, Klare [9] described the four most commonly used readability formulas: the Flesch Reading Ease Index [4], the Fry Index [5], the Dale-Chall Readability Formula [2], and the Flesch-Kincaid Grade Level (GL) Score [8]. These formulas test readability by employing two independent variables: syntactic and semantic complexity. Syntactic complexity is measured in terms of sentence length, while semantic difficulty is differently measured in the four approaches: three of them (Flesch, Flesch-Kincaid and Fry) take into account word length measured in number of syllables, while the Dale-Chall measure assesses semantic difficulty in terms of mean word frequency.

III. Review of commonly used Readability Formulas

Readability tests are designed to predict whether a particular text is appropriate for a particular reader, although they cannot measure the readers comprehension abilities directly. Additionally, text features like the complexity of the ideas, cohesion and coherence cannot be evaluated. Today, a considerable number of readability measures are available, most of which measure characters per word, words per sentence, sentence and paragraph statistics. Some of the most widely used readability formulas that are available for English and Greek are described in the following section.

A. Readability formulas available for English

1) The Coleman-Liau Readability Formula (The Coleman-Liau Index): The ColemanLiau Readability Formula [15] is designed to approximate the usability of a text. It provides word statistics based on numbers of characters rather than numbers of syllables. Its rationale is that instead of using syllable/word and sentence length indices, computerized assessments understand characters more easily and accurately than counting syllables and sentence length. The formula used by the Coleman-Liau index is:

$$CLI = 0.0588 \cdot L - 0.296 \cdot S - 15.8 \tag{1}$$

where L is the average number of letters per 100 words and S is the average number of sentences per 100 words.

2) SMOG Readability Formula (1969): SMOG [11] is a widely used readability measure, commonly used for checking health messages. The mathematical formula used in SMOG is:

$$grade = 1.0430\sqrt{NP \times \frac{30}{NS} + 3.1291} \tag{2}$$

where NP is the number of polysyllabic words and NS is the number of sentences.

3) FOG Index Formula (1952): The Gunning FOG Index Readability Formula [6] is considered a considerably accurate readability measure. The rationale behind the specific measures it employs is that short sentences written in Plain English achieve a better score than long sentences written in complicated language. The ideal score for readability with the Fog index is 7 or 8. Anything above 12 is too hard for most people to read. The formula used in FOG is:

$$0.4\left[\left(\frac{words}{sentences}\right) + 100\left(\frac{complex\ words}{words}\right)\right] \tag{3}$$

4) Flesch Reading Ease Scale: The Flesch Reading Ease Scale [4] is the most commonly used readability formula. It produces readability scores on a scale from 0 (very difficult to read) to 100 (very easy to read). The mathematical formula used in the Flesch Reading Ease Scale is:

$$206.835 - 1.015\left(\frac{words}{sentences}\right) - 84.6\left(\frac{syllables}{words}\right) \tag{4}$$

The scores produced by the formula in 4 are mapped on seven scale levels that enable their interpretation.

B. Readability formulas adapted to Greek

The four most common readability indicators (Flesch Reading Ease [4], Flesch Grade level [8], SMOG [11] and Gunning FOG Index [6]) have been used in the context of creation and construction of the software GRVAL 1.1. GRVAL 1.1 is primarily an automated process of inference as to the degree of readability of Modern Greek texts. It enables the evaluation of the degree of difficulty of examinations texts with the use of a very simple tool, available online at http://www.greek-language.gr/greekLang/modern_greek/foreign/tools/readability/index.html.

C. Shortcomings of the readability formulas

The readability formulas mentioned so far all overlook important variables that determine the linguistic complexity of a text. These include discourse characteristics, density of information, inferential requirements, rhetorical structure, text genre, complexity of ideas etc. Additionally, reader-related variables are also overlooked, such as motivation, cultural background and general world knowledge. For these reasons, readability formulas have often been criticized and considered overly simplistic [13] with regards to the complexity of what is being assessed, especially due to the fact that critical variables are not taken into consideration.

IV. A Model for the Reading Learning Process

Our goal is to construct text classification algorithms which will enable us to sort different texts based on their difficulty for a particular user. Central to our approach is the notion of the *user model* for users with dyslexia.

A. User Modelling

Not all children with dyslexia demonstrate the same set of difficulties. As a consequence, not all children make the same reading errors and, in addition, even if they make the same type of reading errors the severity may be different. The same applies to spelling errors (dysorthographia). The user model includes, among other things, the error types the user is likely to make and their severity, as well as information related to the learning history and progress during the usage of the system.

User Modeling is based on the following, simple, idea: by having information about a specific individual a given computer system can make decisions which are best suited to that individual. Any user model consists of three components; the data being stored about attributes of a user, the algorithms which process this data to affect change on the computational environment and the method by which the user model is obtained and updated.

The content classification module makes use of the user model since, by tracking the specific individual difficulties a given child has, it can provide her appropriate texts for study. Ideally, this is what teachers would like to do in their classrooms. However, the time necessary to interpret the user model of each child in a class, and subsequently produce an individual teaching plan appropriate for that child's specific difficulties and skills for each lesson, is beyond the time resources of nearly all teachers. However, this is something well within the abilities of a computer using a *user modeling component*.

Next, we describe the basic aspects of the user modeling component and the reasons that make this component central to the content classification module.

The user model is intended to provide data to other components through holding information about a given child's linguistic abilities and weaknesses. The full description of the User Model can be found in [16]. For the purposes of this document, we present a high level description of the linguistic difficulties as they are organized into lists of *difficulty categories* (the data contained in these lists also referred to as *profile entries*). We also explain the notions of severity, working index and tricky words.

User Profile Entries: Each user profile entry refers to a particular linguistic problem that a child may have and/or may work on. User profile entries are grouped into *difficulty categories* based on the type of linguistic difficulties they cover In addition, the experts have sorted the profile entries in each category based on their difficulty (or the order in which they are addressed when reading is being taught) in ascending order.

The user model can be considered to be a two-dimensional array incorporating the following information:

1) Each *cell* (also referred to as *profile entry*) of the array includes a description of a single specific difficulty (problem).
2) The i-th row contains only problems of a specific linguistic difficulty category
3) The problems in the i-th row are placed starting from the easiest (leftmost) to the most difficult (rightmost)

The profile entries are language related. Next, we briefly present the linguistic difficutly categories that are covered for the English and the Greek languages.

English Linguistic Difficulty Categories:

1) Syllable division: the difficulty some children have in dividing longer words into smaller chunks (i.e. syllables) which are more manageable.
2) Vowel sounds: refers to the challenge that occurs due to the fact that, in English, there are many vowel sounds which share the same letters (e.g. "**i**" in "did" vs "**i**" in "ivy").
3) Suffixing
4) Prefixing
5) Grapheme/phoneme correspondence: similar to vowel sounds but with consonants (e.g. the phoneme /sh/ appears as "**sh**" in "shop" and "**s**" in "sure").
6) Letter patterns: the difficulty some letter patterns have (e.g. "**mb**" in "bomb").
7) Letter names: children needs to learn the names of the letters in the alphabet.
8) Irregular/sight words: those words which do not follow any of the patterns within English (e.g. "sword").
9) Confusing letter shapes: some graphemes are visually similar (e.g. "**b**" and "**d**") which can be challenging for children with dyslexia.

Greek Linguistic Difficulty Categories:

1) Syllable division
2) Phonemes (Consonants): some words may be confused with others due to a sound similarity among them. This category contains only problems caused by sound similarity of consonant letters.
3) Phonemes (Vowels): same as above, but in this category we consider only problems caused by sound similarity of vowel letters.
4) Suffixing (Derivational)
5) Suffixing (Inflectional / Grammatical)
6) Prefixing
7) Grapheme/phoneme correspondence
8) Grammar / Function words

Severity Level: We define the *severity level* of a profile entry to be an integer in the range $[0 \ldots 3[$ that encodes whether the difficulty *always occurs* (3), *sometimes occurs* (2), *rarely occurs* (1) or *never occurs* (0).

Working Index: To fully describe a user profile we associate each linguistic difficulty category with a working index. For example, the Syllable Division category includes 20 entries for the Greek Profile. Each entry corresponds to a specific instance of a syllable division difficulty and it has been positioned in the row in order of learning complexity. This means that if, say, a child is currently working on the 6-th entry, then she has already worked on entries 1-5 (or has acquired the corresponding skills to a satisfactory degree) and is currently working on the specific language skill represented by the 6-th entry.

Tricky-Words List: The system also allows a user to store a personalized word bank. This is a list of words that is created by each user. Other components of the iLearnRW system (most notably "reader"-applications) that allow her to identify and store words that she "struggles" with.

V. Classification of words/text

In order to describe the TCM we first need to specify when a word or a text is considered to be difficult. To achieve that, we introduce some metrics which take into account the user profile.

A. Word Related Functions

We first start by defining three functions that describe profile and word properties more formally. For simplicity and without loss of generality, we assume that the profile is a two dimensional table. So, each entry of the profile is referred to by two indices (i, j).
When a word has a structure that falls into the description of the (i, j)-th profile entry we say that the word *matches problem* (i, j). In the rest, we always assume that indices i, j refer to a valid profile entry.

We denote by $\mathcal{W}$ the set of all possible words (English or Greek), by $\mathcal{T}$ the set of all possible texts (English or Greek) and by $\mathcal{P}$ the set of all possible users profiles. We define three mathematical functions that will be used to derive the *score* of a word:

Definition 1 (Hit function): Let $hit : \mathbb{N} \times \mathbb{N} \times \mathcal{W} \rightarrow \{0, 1\}$ be an indicator function such that $hit(i, j, p)$ returns 1 if there is at least one profile entry (i, j) in profile $p \in \mathcal{P}$ so that the word $w \in \mathcal{W}$ matches it and, 0 otherwise. Note that if a word matches the same profile entry for more than one reasons, then it is counted only one time.

Definition 2 (Severity function): Let $severity : \mathcal{P} \times \mathbb{N} \times \mathbb{N} \rightarrow \{0, 1, 2, 3\}$ be the function that its value, $severity(p, i, j)$, returns the severity of the profile $p \in \mathcal{P}$ that corresponds to profile entry (i, j).

Definition 3 (Working Index function): Let, $workingIndex : \mathcal{P} \times \mathbb{N} \rightarrow \mathbb{N}$ be the function that given a profile $p \in \mathcal{P}$ and an integer i returns the the working index of a profile that corresponds to the i-th linguistic difficulty category. Note that i has to be smaller or equal to the number of linguistic difficulty categories and the result is bounded by the length of the i-th profile row.

B. Classification of Words

We are now able to firstly define the word score based on which we then characterize a word as *difficult word*, or *very difficult word*.

The *Word Score* is defined to be the sum of all the severities of the users profile entries matched by the word. A more formal definition follows:

Definition 4 (Word Score):

$$W_{score}(\mathcal{W}, \mathcal{P}) \rightarrow \mathbb{N}$$

$$W_{score}(w, p) = \sum_{i,j} (hits(i, j, w) \cdot severity(p, i, j))$$

As it is easy to see, the bigger the score is the more difficult the word is since in this case either the word matches more problems or it matches problems with higher severities.

Difficult Word: In this section we provide three alternative definitions of the notion of *difficult word*. All of them use the natural assumption that a word is more difficult for the user if it matches many problems or problems with higher severities or problems that are beyond her working index.

Let $w \in \mathcal{W}, p \in \mathcal{P}$ and $W_{score}(w, p)$ be the score of the word for the specific user. The definitions for the notion of difficult word follow:

Definition 5: The word $w \in \mathcal{W}$ is considered to be *difficult* for profile $p \in \mathcal{P}$ if there is at least on pair of indices i, j such that $hit(i, j, w) = 1$ and $severity(p, i, j) > 0$.

According to the above definition a word is considered to be difficult if it matches at least one users problem with severity greater than 0.

Definition 6: The word $w \in \mathcal{W}$ is considered to be *difficult* for profile $p \in \mathcal{P}$ if $W_{score}(w, p) > 1$.

This means that a word is difficult when it matches with at least two user's problems of severity equal to 1 or with at least one problem of severity greater than 1.

Definition 7: The word $w \in \mathcal{W}$ is considered to be *difficult* for profile $p \in \mathcal{P}$ if there is at least on pair of indices i, j such that $hit(i, j, w) = 1$ and $workingIndex(p, i) \leq j$.

The last means that a word is considered to be difficult if it matches at least one user's problem that is beyond his/her current working indices.

Very Difficult Word: After giving several characterizations for the notion of a difficult word we now provide a definition for words that are considered to be very difficult. By having such a characterization for each word, we can take advantage of it by treating these words in a special manner when they are met within a text.

Definition 8: The word $w \in \mathcal{W}$ is considered to be *very difficult* for profile $p \in \mathcal{P}$ if $W_{score}(w, p) \geq 6$.

Note that for a word to be assigned of a score greater of equal to 6 it has to either match at least two problems of the greatest possible severity (i.e. 3) or at least 3 problems. For a word that matches only problems of severity 1, it has to match at least 6 problems in order to be classified as very difficult.

Text Score: Based on the presented quantification on word metrics, we are now able to define the text score (denoted by T_{score}) which, informally, is a positive number that describes the difficulty of the text. After having such a metric we can rank texts by sorting them according to their T_{score}'s.

Definition 9: Let $appearances : \mathcal{T} \times \mathcal{W} \rightarrow \mathbb{N}$ be a function which on input $t \in \mathcal{T}$ and $w \in \mathcal{W}$ returns the number of appearances of word w in text t.

Definition 10: Define $T_{score} : \mathcal{T} \times \mathcal{P} \rightarrow \mathbb{R}$ to be the iLearnRW-score for text $t \in \mathcal{T}$ with respect to profile $p \in \mathcal{P}$, as follows:

$$T_{score}(T, p) = \sum_{w \in t} \frac{appearances(t, w) + 1}{2} \cdot W_{score}(w, p)$$

The above formula that we use to calculate the text score captures, in a high level description, the magnitude of the user severities on problems areas that are relevant to the words in the text. That is, the more problematic words the text has (with respect to the specific user), the bigger its T_{score} is.

The term $\frac{appearances(t,w)+1}{2}$ is derived as follows: we suppose that when a word is repeated in the text then its weight (i.e. its difficulty) reduces at each repetition. That is, if a reader sees a word multiple times inside a text then the word starts to become more familiar to her. More precisely the i-th appearance of a word contributes $\frac{appearances(t,w)+1-i}{appearances(t,w)}$ of the word's W_{score}. Doing the sum for all i, we get the total weight of a word to be $\frac{appearances(t,w)+1}{2}$.

VI. Applications

In this section we present an application presented in the 1-st annual review of the iLearnRW project which demonstrates the integrated usage of the text classification component. The application loads the profile of an individual user and it supports the following functionality: (i) profile viewer, (ii) file explorer with text ranking, (iii) word analysis and (iv) text analysis. We present snapshots form the *profile viewer* and the *text analysis* screen (which is a superset of the *word analysis* screen). Figure 2 shows the profile viewer tab of the application. The profile viewer provides a visualization of the user profile loaded in the application. The loaded profile corresponds to a Greek child and is composed of nine linguistic difficulty categories (the rows of the table) each of which is broken down into a list of specific problems (profile entries; the cells of each row). Each profile entry contains the severity of the entry and is colored accordingly (green denotes severity rate "0" while red denotes severity rate "3"). In addition, a single profile entry is emphasized in each linguistic difficulty category (row) by being drawn with a bold black border, denoting the working index of the user in the corresponding linguistic category.

Figure 3 shows the Text Analysis tab of the demo application. The text to be analysed is loaded in the left panel of the tab. The two-dimensional array on the left displays the profile entries in color variation between white and red. The rule to color an entry is, roughly, the following: the larger the number of words in the text having structure that matches to the entry's corresponding problem, the higher the redness of the cell is.

Fig. 1: The profile of a Greek user is loaded in the Profile Viewer tab of the demo application of the iLearnRW project.

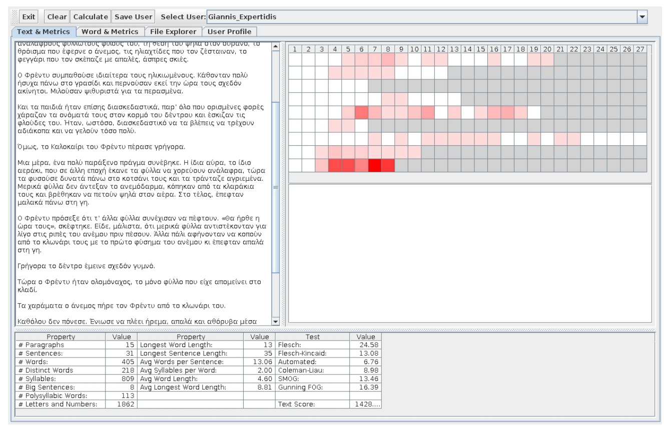

Fig. 2: A Greek text is loaded and analyzed by the Text Analysis demo appication of the iLearnRW project.

Note that by combining information on the severity of the "highly red" profile entries, we can draw conclusions on how difficult is a particular text for a specific user and, moreover, pinpoint the nature of the potential difficulties. Finnaly,he lower panel displays the values of different metrics on the text (e.g., numbers of syllables, words, paragraphs, number of difficult and very difficult words, Coleman-Liau index, SMOG index, FOG index, Flesch Reading Ease scale, several averages etc.) providing an overview of the text characteristics.

VII. Preliminary Evaluation Results

The Text Classification Module (TCM) was tested in a small-scale pilot study, aiming to explore the correlation between the TCM performance in classifying text with respect to difficulty and the reading performance of children with dyslexia. Specifically, it was hypothesized that, if TCM can produce a reliable estimate of the difficulty of a text with respect to linguistic criteria specific to dyslexia, then texts that classified as hard by the TCM will pose greater difficulties to children with dyslexia than texts that are classified as easy. In other words, TCM classification scores will coincide with how difficult a text appears to children with dyslexia.

The pilot study recruited 10 children diagnosed with specific learning disabilities / dyslexia (LD-D) and 10 children with no reported learning difficulties as a control group (CG).

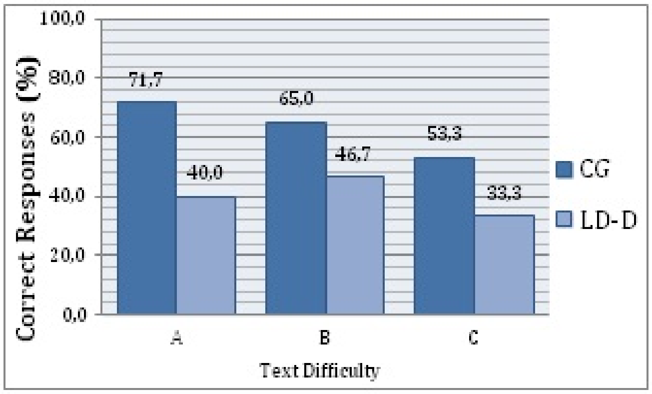

Fig. 3: Childrens performance in Text Comprehension Text Difficulty: A=Easy, B=Medium, C=Hard

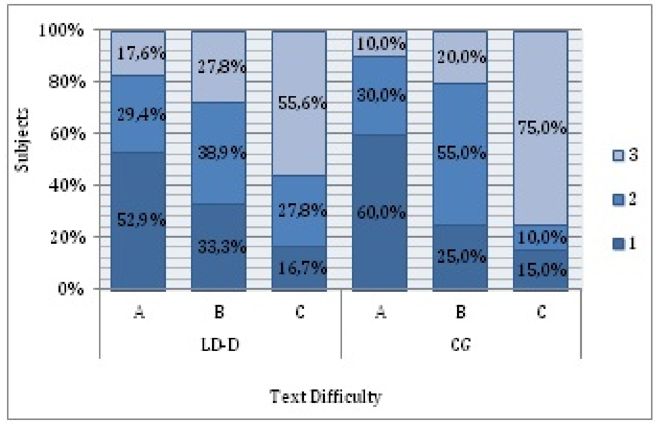

Fig. 4: Childrens rating on text difficulty (1=easy, 2=medium, 3=hard) Text Difficulty: A=Easy, B=Medium, C=Hard

The LD-D group age range was 10;8-12;1 (mean age 11;6, SD = 0;6), while the CG age range was 10;10-12;0 (mean age = 11;6, SD = 0;5). The materials included six texts drawn from school materials or online educational materials designed for primary-school children. The texts were tested through the TCM and difficulty scores were obtained for each of them, based on which they were classified as easy, medium or hard, so that 2 texts were included in each category. They were presented to the children in two sets of three texts (one from each difficulty level) in two different sessions. Two measures were used to define the childrens difficulty in handling the texts: (a) their performance in three multiple-choice questions on each text, and (b) their raw rating of the text difficulty. The multiple-choice questions were created to address three aspects of each text: general comprehension, vocabulary and sentence comprehension. The childrens rating on the texts was obtained by asking them to place the three texts presented in each session in order according to difficulty, writing the number 1 to the easiest one, the number 3 to the hardest one and the number 2 to the one in between.

Preliminary analyses of the results were performed on the two measures. The results on the childrens comprehension are illustrated in Figure 4.

The performance of the CG seems to be affected by the text difficulty as determined by the TCM, while the LD-D group exhibits a less clear performance. However, analyzing childrens rating provides a clearer picture, as shown in Figure 5.

It thus seems that both groups ratings on the texts are better correlated with the classification made by the TCM than performance in text comprehension. This can be attributed to the nature of the linguistic criteria used by the TCM, which are mainly relevant to formal aspects of texts, phonological and morphological properties, mostly affecting decoding skills rather than reading comprehension.

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References

[1] P. Blache, *A Computational Model for Linguistic Complexity*, In proceedings of the First International Conference on Linguistics, Biology and Computer Science, 2011.

[2] J.S. Chall and E. Dale, *Readability Revisited: The New Dale-Chall Readability Formula*, Cambridge, MA: Brookline Books, 1995.

[3] J.S. Chall, G.L. Bissex, S.S. Conard and S.H. Harris-Sharples, *Qualitative Assessment of Text Difficulty: A Practical Guide for Teachers and Writers*, Cambridge, MA: Brookline Books, 1996.

[4] R. Flesch, *A New Readability Yardstick*, Journal of Applied Psychology, 32, pp. 221-233, 1948.

[5] E.B. Fry, *A Readability Formula that Saves Time*, Journal of Reading, 11, pp. 513-516, 1968.

[6] R. Gunning, *The Technique of Clear Writing*, New York: McGrawHill, 1952.

[7] K. Hess and S. Biggam, *A Discussion of "Increasing Text Complexity"*, An article produced in partnership with the New Hampshire, Rhode Island, and Vermont Departments of Education, 2004.

[8] J.P. Kincaid, R.P. Fishburne, R.L. Rogers and B.S. Chissom, *Derivation of New Readability Formulas (Automated Readability Index, Fog Count, and Flesch Reading Ease Formula) for Navy Enlisted Personnel*, CN-TECHTRA Research Branch Report, 1975.

[9] G. Klare, *Readability. In: P.D. Pearson, R. Barr, M.L. Kamil, and P. Mosenthal (eds.), Handbook of Reading Research*, NY: Longman, pp. 681-744, 1984.

[10] M. Lipson and K. Wixson, *Assessment and Instruction of Reading and Writing Difficulty: An Interactive Approach (3rd ed.)*, Boston: Allyn & Bacon, 2003.

[11] G.H. McLaughlin, *SMOG Grading - A New Readability Formula*, Journal of Reading 22, pp. 639-646, 1969.

[12] M. Miestamo, *Grammatical Complexity in a Cross-linguistic Perspective*, In: M. Miestamo, K. Sinnemaki and F. Karlsson (Eds.), Language Complexity: Typology, Contact, Change, pp. 23-42. Amsterdam, Philadelphia: Benjamins, 2008.

[13] M.H. Sawyer, *A Review of Research in Revising Instructional Text*, Journal of Reading Behaviour, 23(3), pp. 307-333, 1991.

[14] B. Szmrecsanyi and B.Kortmann, *Introduction: Linguistic Complexity - Second Language Acquisition, Indigenization, Contact*, In B. Kortmann and B. Szmrecsanyi (Eds.), Linguistic Complexity: Second Language Acquisition, Indigenization, Contact. De Gruyter, 2012.

[15] M. Coleman and T.L. Liau, *A Computer Readability Formula Designed for Machine Scoring*, Journal of Applied Psychology, Vol. 60, pp. 283284, 1975.

[16] D. Gooch, M. Vasalou, D. Lukes, J. Flowers, and L. Benton, *User modelling for users with dyslexia and dysorthographia*, iLearnRW Deliverable 4.1. Available from www.ilearnrw.eu/deliverables.