CONCEPTUALIZING A FRAMEWORK FOR ANALYSING COLLEGE STATISTICS TEXTBOOKS IN TERMS OF TEXT ACCESSIBILITY

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ABSTRACT

This article develops an analytical framework for analysing college (tertiary) statistics textbooks in terms of text accessibility by integrating the text, the reader, and the content into the framework. Five accessibility attributes of science texts were adapted to conceptualize the accessibility of statistics texts. For each accessibility attribute, two components were proposed by referring to the literature on the readability of mathematics texts as well as the characteristics of statistics. The feasibility of the framework is demonstrated by analysing sample statistics texts. The contributions and potential of the framework are discussed.

Keywords: *Statistics education research; College statistics; Content area reading; Text accessibility; Textbook analysis*

1. INTRODUCTION

Reading to learn in content areas has been emphasized for several decades (Richardson et al., 2006). For college (tertiary) students, the ability to learn through reading is essential as the more they advance in their studies, the more they need to rely on the ability to learn from academic textbooks independent of the instructor (Alfassi, 2004; Maclellan, 1997). College students, however, often see reading as being useful for specific assessment in a course rather than as a thought-provoking approach to accessing knowledge (Manarin, 2019). In contrast, most college students need to learn statistics as part of their lifelong learning since it is a useful skill for professionals in various disciplines (Scheaffer & Stasny, 2004).

Reading statistics textbooks, similar to reading textbooks in other content areas, involves the interaction or transaction between a reader and a text situated in a particular context (Rosenblatt, 1986). Accordingly, characteristics of statistics textbooks, as a text, might influence readers' reading activity. These characteristics include the density of statistical ideas (Cobb, 1987), lexically ambiguous terms and phrases (Kaplan et al., 2009; Lesser et al., 2013; Lesser & Winsor, 2009), and complexity of graphical displays (Friel et al., 2001; Shah & Hoeffner, 2002).

Textbook analysis is still rare in the area of statistics education, particularly at the college level. Few studies have suggested that readability of statistics textbooks for college students could be hindered for some extent by sophisticated mathematical presentation (Huberty & Barton, 1990). Text readability is known as an essential index of reading comprehension and is used to evaluate the match between a reader and a text. It has also been suggested as an important criterion for analysing statistics texts used in education textbooks (Harwell et al., 1996; Huberty & Barton, 1990). The literature shows, however, that readability frameworks are not yet widely used, and their limitations have been acknowledged, such as surface recognition of words as well as the neglect of writing styles and the inherent complexity of the topic (Lesser et al., 2016). Multiple criteria are necessary for evaluating the appropriateness of texts for readers (Benjamin, 2011).

Gunning (2003) proposed text accessibility as a broader concept of text readability, considering the contexts of readers and texts, instead of merely relying on the surface features of the text and the quality of the writing style. The contexts of readers and texts are prominent given that different content in the

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text and reading goals may require different reading strategies to comprehend the text (Fang & Schleppegrell, 2010; Weinberg & Wiesner, 2011). Accordingly, this study aimed to propose a text accessibility framework for analysing statistics textbooks. Since the framework is specified for college statistics textbooks, the intended readers of the textbooks are college students and the intended content is statistics.

2. THEORETICAL BACKGROUND

2.1. SOURCES GUIDING THE DEVELOPMENT OF OUR ACCESSIBILITY FRAMEWORK FOR STATISTICS TEXTS

Reading in content areas can be approached from various perspectives, including cognitive, sociocultural, linguistic, and critical (Fang, 2012). The cognitive approach was adopted by McTigue and Slough (2010) to propose the accessibility attributes of science texts. Since the attributes are supported by cognitive theories, they might be applicable to other content areas including statistics. More specifically, statistics and science have similar philosophical thinking based on empiricism (Popper, 2014). Nonetheless, to adapt the attributes to statistics texts, specific aspects of statistics need to be considered.

Due to the limited studies on reading statistics texts and considering applied mathematics as one potential view of statistics, the readability components of mathematics texts proposed by Shuard and Rothery (1984) were considered, in addition to the characteristics of statistics textbooks suggested in the literature. In the following, we introduce the five accessibility attributes of science texts (McTigue & Slough, 2010), followed by critical components related to the readability of mathematics texts (Shuard & Rothery, 1984).

Five attributes of text accessibility for science texts. McTigue and Slough (2010) synthesized five key accessibility attributes: the text concreteness, the voice of the author, a coherent writing structure, selective use of visual information, and integrated verbal and visual information. Referring to dual coding theory (Sadoski & Paivio, 2004), McTigue and Slough (2010) stated that “Concrete language, in contrast to abstract [language], naturally evokes images and corresponding cognitive connections between the text and images” (p. 218). The *text concreteness* was addressed as an important factor for overall comprehension and recall of science texts and enhancing students’ interest. For instance, presenting statistical data as numbers in context is more concrete for students than presenting numbers without context.

Like text concreteness, *the voice of the author*, which is also referred to as the voice of science, is related to readers’ interest and engagement. Beck et al. (1995) defined the function of voice as the representation of qualities of text that make it speak to the reader. Text that speaks to a reader minimizes the distance between the reader and the information in the text because the distance may inhibit a reader’s construction of knowledge from the text (Beck et al., 1995). They further suggested that giving voice to texts, particularly social studies texts for elementary school students, would involve making text situations more dynamic by using verbs that represent more concrete action (activity), including some of the conversational tone of oral language (orality), and highlighting several kinds of relationships (connectivity). Accordingly, an accessible science text is expected to have a discernible author voice to make the scientific ideas clear to the reader and be energized without diluting the science content (McTigue & Slough, 2010). For instance, the author should use sufficient and effective concrete supporting details to make explicit connections between the intended readers’ prior knowledge and one abstract concept in the text.

Coherent writing structure, or organizing text in a clear and logical manner, benefits readers by helping them develop a coherent understanding of the text (Lehman & Schraw, 2002; Meyer & Freedle, 1984). In addition, signalling, such as adjunct questions, informative headings, and pointer words, may increase comprehension by reducing readers’ cognitive load of processing information and guiding readers to connect pieces of information (McTigue & Slough, 2010). This perspective is consistent with Kintsch's (2013) construction-integration theory; that is, one way to help readers make an appropriate inference is by providing clues to the links between discrete units of information in the text. In adapting the attribute to statistics texts, the focus of the attribute of coherent writing structure of statistics text is on the links represented by deep coherence between the ideas presented.

As for *visual information*, McTigue and Slough (2010) emphasized that the graphics used in science texts should represent the type of graphics used in authentic science inquiry, and suggested providing more common representations in textbooks, such as tables, hybrid diagrams, picture glossaries, flowcharts, and graphs. Moreover, visual information in science textbooks is critical for depicting dynamic processes and clarifying a complex system. Similarly, statistical graphs are used to represent the pattern of variations in contexts. The choice of visual information influences readers' construction of meaning and should be made to match the intention of the verbal information in texts in order to enhance text accessibility.

Two keys to *integrated visual and verbal information* are further identified by McTigue and Slough (2010). First, visual and verbal information should be placed near each other, preferably in the same visual field. Second, the use of verbal information within and around visual information should assist readers in constructing meaning. For instance, the effective use of captions and labelling as well as notations can direct readers' attention to the visual information.

Critical components related to the readability of mathematics texts. Shuard and Rothery (1984) analysed the possible critical components affecting difficulties experienced by students in reading mathematics texts and identified some criteria to improve the readability of texts. The components encompass the content features of mathematics texts and the visual appearance of the text. The content features were categorized as verbal elements (i.e., vocabulary and syntax), nonverbal elements (i.e., symbols and graphic language of diagrams, pictures and illustrations), as well as the way in which the content meaning is presented in the text (i.e., flow of meaning).

The first critical component of text readability, the *verbal elements*, may include unfamiliar words, the confusing meaning of Mathematical English (ME), a lack of context words, and lexical familiarization. More specifically, three categories of words in ME were identified: (1) words having a similar meaning in ME and Ordinary English (OE), (2) words having a meaning only in ME, and (3) words having a different meaning in ME from their meaning in OE. The three categories of words generate different difficulty levels of comprehension and are related to text concreteness (McTigue & Slough, 2010).

Second, regarding the *nonverbal elements*, Shuard and Rothery (1984) suggested that careful attention is needed in arranging text and diagrams since they need very detailed processing in mathematics. Similar to that for science texts (McTigue & Slough, 2010), the diagrams in mathematics text should be placed close to the text to help readers refer backwards and forwards between the text and the diagrams. The use of conventions of shading, colouring, scale, and motion is also essential to show the ideas in a mathematical diagram. The highlighted layouts of diagrams and their connections with verbal elements are emphasized, which resonate with both visual information and the integrated visual and verbal information attributes.

Third, the *way in which the content meaning is presented* in the text may also affect reading difficulty. To enable readers to reach new understandings when reading mathematics texts, the text must have a clear "story line" or flow of meaning as the arguments are arranged within a passage. Three types of meaning units were distinguished as (1) the statements which are made in the text, (2) the statements which can only be discovered in questions or tasks, and (3) the meaning units which have to be inferred from the texts or from the readers' background knowledge. The first two types of meaning units aim at the connections within text and are thus related to the attribute of coherent writing structure. The third type concerns prior knowledge, which is also a focus of the voice of the author.

3. ACCESSIBILITY FRAMEWORK OF STATISTICS TEXTS

To develop an accessibility framework of statistics texts, we adapted the five accessibility attributes of science texts (McTigue & Slough, 2010). The critical components of accessibility of statistics texts were then derived by the integration of critical components of reading mathematics texts and the features of statistics texts suggested in the literature (see Table 1). We focused on two critical components for each attribute induced from significant literature. The significance of each component is argued by referring to important cognitive theories (i.e., construction-integration, dual coding, connectionist, multimedia learning, and cognitive load theories).

Table 1. The derivation of components of accessibility of statistics texts

Attributes of accessibility of science text (McTigue & Slough, 2010)	Critical components of reading mathematics texts (Shuard & Rothery, 1984)	Features of statistics texts (Literature on statistics and reading)
Text concreteness	Three categories of words in Mathematical English	Focusing on statistical terms that may lead to linguistic challenges for readers (e.g., Dunn et al., 2016; Kaplan et al., 2012; Rangecroft, 2002); and connecting reader's prior understanding to the meanings of statistical terms which may help reader understanding (Berenson, 1997).
Voice of authors	The meaning units that have to be inferred from the texts or from the readers' prior knowledge	Focusing on statistical cognitions (Garfield & Franklin, 2011; Lei & Yang, 2012), which connect reader's cognition to statistical concepts and meanings of data (Idris & Yang, 2017), which connect reader's experience to statistical contexts.
Coherent writing structure	The statements that are made in the text or that can only be discovered in questions or tasks	Focusing on the connections of a statistical concept to other statistical concepts (e.g., Franklin & Garfield, 2006; Rossman et al., 2006) or to data contexts (Garfield, 2003) that could increase text coherence.
Selective use of visual information	The highlighted layouts of diagrams	Focusing on types of visual information used in statistics, which may have different effects on students' recognition of statistical concepts (Cooper & Shore, 2010), and graph processing (Vekiri, 2002); and purposes of various types of visual information in statistics (e.g., Friel et al., 2001; Graham, 1987).
Integrated visual and verbal information	The connections of diagrams with verbal elements	Focusing on placing the visual and related verbal information close to each other (Hegarty & Just, 1993; Mayer & Moreno, 2003) and providing descriptive texts within the graphs (Friel et al., 2001; Mayer & Moreno, 2003), which benefit a reader's comprehension.

To describe how the framework can be operationalized, we provide an example analysis of college statistics texts. In each subsection, the components of each attribute of the framework are first described and then are applied to a given set of texts. Since readers' experiences are related to text accessibility, we must specify the population of the readers for whom we are analyzing the texts. In the example analysis, the intended readers of the statistics texts are English as a Foreign Language (EFL) pre-service teachers in Indonesia. The next step is to define the unit of analysis of the texts in which the components of accessibility attributes are to be investigated. Defining the analysis unit is important when content analysis is to be applied. We defined one analysis unit as one type of text with one focused statistical term. Examples of classifications of the types of text in a college statistics textbook include introductory text, explanatory text, worked example, or practice.

For the example analysis, we extracted sample texts on the topic of boxplots from *Introduction to the Practice of Statistics* (IPS) (Moore et al., 2009, pp. 37–38). Five analysis units were identified from the sample texts, which were labelled Unit 1 to Unit 5. Unit 1 introduced the boxplot by showing sample boxplots generated from previously given data:

The five-number summary leads to another visual representation of a distribution, the boxplot. Figure 1.19 shows boxplots for both city and highway gas mileages for two groups of cars.

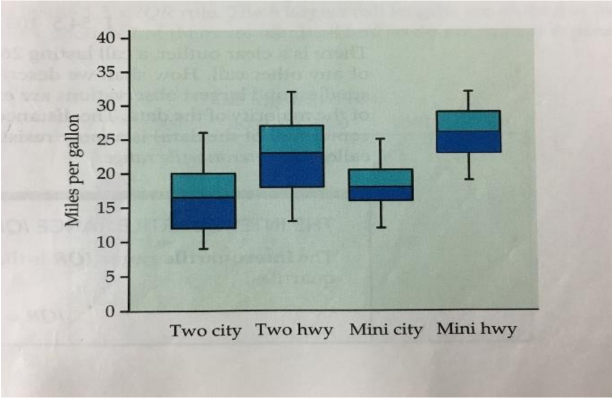

Figure 1.19. Boxplots of the highway and city gas mileages for cars classified as two-seaters and as minicompacts by the Environmental Protection Agency.

Figure 1. Boxplots presented in Introduction to the Practice of Statistics *(Moore et al., 2009, p. 37, Figure 1.19).*

Then, Unit 2 defined boxplots and explained the values represented in each of its components (Moore et al., 2009, p. 38).

A boxplot is a graph of the five-number summary.

- *A central box spans the quartiles Q_1 and Q_3.*
- *A line in the box marks the median, M.*
- *Lines extend from the box out to the smallest and largest observations.*

Next, Unit 3 described techniques to examine the distribution presented in a boxplot and elaborated on the values presented in the boxplot and what they have to tell about a data set (Moore et al., 2009, p. 38).

When you look at a boxplot, first locate the median, which marks the center of the distribution. Then look at the spread. The quartiles show the spread of the middle half of the data, and the extremes (the smallest and largest observations) show the spread of the entire data set.

Unit 4 provided practice for students to construct a boxplot (Moore et al., 2009, p. 38).

Make a boxplot. Here are the scores on the first exam in an introductory statistics course for 10 students:

80 73 92 85 75 98 93 55 80 90

Make a boxplot for these first-exam scores.

Lastly, Unit 5 described the effectiveness of boxplots for comparing distributions (Moore et al., 2009, p. 38).

Boxplots are particularly effective for comparing distributions as we did in Figure 1.19. We see at once that city mileages are lower than highway mileages. The minicompact cars have slightly higher median gas mileages than the two-seaters, and their mileages are markedly less variable. In particular, the low gas mileages of the Ferraris and Lamborghinis in the two-seater group pull the group minimum down.

Accordingly, Unit 1, Unit 2, Unit 3, and Unit 5 were identified as explanatory texts, while Unit 4 was determined to be immediate practice.

3.1. TEXT CONCRETENESS

The concreteness of a text can be determined by its ability to evoke images naturally and the corresponding cognitive connections between the text and images in the reader's mind (McTigue & Slough, 2010). Thus, we relate the concreteness of statistics texts to the ways in which the statistics content is presented in the text, which can help readers to comprehend and recall the contents. More specifically, referring to the content features of mathematics texts (Shuard & Rothery, 1983), we stipulate the statistics content as statistical terms (verbal elements) and exclude the nonverbal elements since the nonverbal elements are discussed separately in the two last attributes of this framework. Therefore, we specify the two components of the attribute of text concreteness as meanings of statistical terms related to natural language (linguistic meanings) and to intended readers' prior understanding (learner's meanings).

Linguistic meanings of statistical terms. Since statistics uses much mathematics terminology, the categories suggested by Shuard and Rothery (1984) are considered relevant for statistics. There are two additional categories specified for statistical terms: words that occur in both Statistics English (SE) and Mathematical English (ME), but have a different meaning in SE from their meanings in ME (e.g., estimate, significant, range) (Rangecroft, 2002) and words from discipline-specific English (Dunn et al., 2016). The possible different meanings of one term in ME, SE and OE may lead to linguistic challenges for readers (Dunn et al., 2016; Kaplan et al., 2012).

Even for SE with comparable meanings to OE, the meanings in statistics are usually more precise (Thompson & Rubenstein, 2000). For example, in statistics the term *average* is usually used to describe the process of finding the mean of a data set, in daily language it may be used to describe what is *typical* and what is *normal* (Kaplan et al., 2009). When facing such terms, students may incorrectly associate the terms with those they use in daily life (Kaplan et al., 2009, 2010; Lesser et al., 2013; Lesser & Winsor, 2009).

For example, the focused statistical term provided in the sample texts from IPS discussed previously is *boxplots*. The term is comprised of two words: "box" and "plots", both of which occur in OE. The meaning of "box" in OE could be related to the shape of the boxplots, whereas the meaning of "plot" in OE is the series of events in film, literature or writing, which is different from the meaning in Statistical English (SE). There are no linguistic meanings of boxplots addressed by the authors in all five units selected from IPS.

For comparison, other sample texts from *Fundamentals of Statistical Reasoning in Education* (FSRE) (Coladarci et al., 2004) were taken. In the sample text, the linguistic meaning of boxplots was addressed by relating the word "box" and characteristics of the representation to the appearance of the boxplot (Coladarci et al., 2004, p. 49). The authors stated:

> *This device derives its name from the "box" in the middle, which represents the middle 50% of scores: [t]he box extends from the 25th percentile (or Q_1, the first quartile) to the 75th percentile (or Q_3, the third quartile). The line you see running through the box is the "median" score, which is equal to the 50th percentile (Q_2): half of the scores fall below, half of the scores fall above. … The "whiskers" that are affixed to the box show the range of scores.*

Learner's meanings of statistical terms. Making connections to the students' prior experiences in statistical concepts (e.g., Hiedemann & Jones, 2010; Wiberg, 2009) has been suggested when designing learning materials for college statistics (Idris, 2018). More specifically, making connections among students' prior understanding of the terms and the specialized meanings in text would be helpful for students (Berenson, 1997). Readers' prior understanding of statistical terms, which include the terms they have learned or used in daily life or in a particular field of study, is considered essential for text concreteness, since it would be activated during the process of reading in both the construction and integration phases (Kintsch, 1998, 2013).

In the sample texts of IPS, no learner's meanings of boxplots is addressed. In contrast, the FSRE addressed the learners' meaning of boxplots by connecting it to different statistical terms with similar meanings, such as the *box-and-whiskers plot*. The authors mentioned in the text, "*For this reason, such a graph also is called a box-and-whisker plot. For convenience, we use the shorter name*" (Coladarci et al., 2004, p. 49). Since the term box-and-whisker plot was learned by the Indonesian EFL pre-service teachers in their high school mathematics, FSRE could be more concrete than IPS for Indonesian EFL pre-service teachers in the topic of boxplots.

3.2. THE VOICE OF STATISTICS

The function of voice is to represent the qualities of text that make it speak to the reader (Beck et al., 1995). Hence, we interpret the voice of statistics as the qualities of statistics content provided to readers by the authors, which can help the readers access the statistics provided in the text. Accordingly, referring to the voice of science proposed by McTigue and Slough (2010), the attribute of voice of statistics aims at making explicit connections between readers and an abstract statistical concept presented in the text. That is, the reader is drawn into the text to make sense of one abstract concept through several perspectives. Making sense of a statistical concept would include understanding statistical basic knowledge, reasoning, and thinking related to the concept (i.e., statistical cognitions; Garfield & Franklin, 2011; Lei & Yang, 2012), as well as understanding data and contexts used in presenting the concept (i.e., meanings of data; Idris & Yang, 2017). The statistical cognition presented in the text would connect the reader's cognition to the statistical concept, while the meanings of data would connect the reader's experience to the statistical contexts.

Hence, we specifically determined the qualities of statistics content to include the types of statistical cognitions and meaning of data provided for readers to make sense of statistics. Two components of the attribute of the voice of statistics are approaches to statistical cognition and approaches to meanings of data.

Approaches to statistical cognition. The outcome of learning statistics should not be limited to understanding procedures without grasping the underlying ideas (e.g., Franklin & Garfield, 2006; Garfield & Ben-Zvi, 2004; Garfield & Franklin, 2011). Accordingly, the different ideas arranged to introduce a statistical concept in statistics texts may be associated with types of statistical cognitions (Garfield & Franklin, 2011). For instance, a statistics text may present basic statistical knowledge, in this case procedural, when introducing the term *mean* by providing a formula followed by showing a worked example. Statistical reasoning can be presented when elaborating arguments about why the mean is a better description of the dataset compared to the median in certain contexts. How these different purposes are presented when introducing a concept can indicate whether statistics content is sufficiently provided in a textbook.

Returning to the sample texts from IPS, statistical cognitions for elaborating the concept of boxplots are presented as the basic knowledge in the first four analysis units, followed by statistical reasoning in the last analysis unit. That is, Unit 1 provided the introduction to a boxplot as a type of visual representation of distribution, Unit 2 defined a boxplot and its components, Unit 3 elaborated the procedure for examining distribution using a boxplot, Unit 4 provided practice to construct a boxplot, while Unit 5 presented statistical reasoning about the usefulness of boxplots for specific situations, and interpretion of the distributions represented in the sample boxplots. As a result, the topic of boxplots was presented by emphasizing basic statistical knowledge and statistical reasoning.

Approaches to meanings of data. Data are required to engage in statistics (Mojica et al., 2018) as statistical concepts cannot be elaborated without connecting to data (e.g., Rossman et al., 2006). Statistics textbooks may address diverse meanings of data when elaborating statistical concepts. For instance, when the term mean is introduced, data as numerical numbers without context might be addressed by focusing on the calculating procedures, while data as numbers in problem contexts can be addressed to elaborate and connect the results of calculation into the data context. How the meanings of data are addressed in statistics texts is essential since they are not only associated with statistical reasoning (Bakker & Gravemeijer, 2004; Konold et al., 2015; Pfannkuch, 2011) and the conception of statistics (Idris & Yang, 2017), but also reflect the attempt to prepare statistically literate citizens (Weiland, 2019), which is the goal of statistics education at the college level (Aliaga et al., 2005).

The approach to meanings of data can be analysed in IPS sample text in Unit 1, Unit 4 and Unit 5, for example, while the other two units do not refer to statistical data. The meanings of data addressed in the units are data as numbers in problem contexts, as numbers without context, and as information for evaluation. Unit 1 addresses data as numbers in problem contexts, as expressed in the second sentence: "*... shows boxplots for both city and highway gas mileages for our two groups of cars*" (Moore et al., 2009, p. 37). Unit 3 addressed data as numbers without context to be utilized for constructing a boxplot. Although the data context is given, it is not related to the procedures nor is it used to interpret the results. Unit 5 addressed data as the information for evaluation, as expressed in the last sentence. As a result, the topic of boxplots in the text provided three types of meanings of data.

3.3. TEXT COHERENCE

Referring to McTigue and Slough (2010), we interpreted a coherent statistics text as a text that provides the overall structure of the statistical concept being elaborated and helps readers to see the overall structure. To show the overall structure of the statistical concepts means enabling the reader to see the statistical concepts as interrelated rather than as isolated pieces. The overall structure of a statistical concept can include its connection to other statistical concepts or data contexts, which should be pointed out when introducing the concept (Franklin & Garfield, 2006; Garfield & Ben-Zvi, 2004; Rossman et al., 2006). The concept and context connections echo the coherent arrangements of the flow of meaning suggested by Shuard and Rothery (1984), and are supported by connectionist theory (Smith, 1996), where coherence is related to connections. Thus, two components of the attribute of text coherence were recognized as concept and context connections regarding approaches to statistical cognitions and approaches to meanings of data.

Coherence of approaches to statistical cognitions. Coherence of approaches to statistical cognitions is specified as the connections of concepts and contexts regarding statistical cognitions. Connecting centre and variability, considering issues about data production, revisiting fundamental ideas whenever appropriate, or emphasizing common elements in data analysis arising in different context situations (Garfield & Ben-Zvi, 2004; Rossman & Chance, 2014) are all beneficial to increasing text coherence.

In Unit 1 of the IPS sample texts, for example, the basic knowledge of boxplots was connected to the concept of five-number summary. Accordingly, Unit 2 and Unit 3 connected basic knowledge of boxplots to other concepts, namely five-number summary, centre, and variability. No connection was presented in Unit 4. Unit 5 connected statistical reasoning about boxplots to the idea of distribution and to the concept of median.

Coherence of approaches to meanings of data. Coherence of approaches to meanings of data is specified as the connections of concepts and contexts regarding meanings of data. Using similar data or data contexts to introduce different concepts could assist students to extend the concepts, apply them in new situations, and develop their understanding on the concepts (Garfield, 2003).

In Unit 1 of the IPS sample texts, the data as numbers in the problem context were connected to that used in a previous part of the text. Similarly, in Unit 5, data as information for investigation were connected to that used in a previous part of the text. Since concept and context connections were provided in these units of example text, it can be concluded that the text showed the boxplot as the interrelated concept and connection within context.

3.4. SELECTIVE USE OF VISUAL INFORMATION

The two components of the attribute of selective use of visual information are types of visual information and purposes of referring to visual information. The two components were assigned by referring to the suggestion by McTigue and Slough (2010) about the importance of matching the visual and the intention of verbal information.

Type of visual information. Since different types of graphs may have different effects on students' recognition of statistical concepts (Cooper & Shore, 2010) and graph processing (Vekiri, 2002), we considered types of visual information used in discussing statistical terms as a component of this attribute. The categories of nonverbal elements presented in mathematics texts proposed by Gunzel and Binterova (2016) were adapted to specify types of visual information in statistics texts. The categories include tables, graphs, and illustrations (photos/drawings). In addition, the combinations of different visual information are commonly presented in statistics texts, such as the combinations of graphs, combinations of tables, and combinations of graphs and tables. In the sample texts, the type of visual information in Unit 1 was a graph (i.e., boxplots in Figure 1.19 of the IPS sample text Unit 1), which was also referred to in Unit 5. The FSRE, however, referred to the combination of two types of graphs, histograms, and boxplots, in discussing the concept of boxplots.

Purpose of visual information. The various types of visual information used in statistics textbooks may have different purposes. As Tufte (1983) wrote: "Graphics reveal data. Indeed, graphics can be more precise and revealing than conventional statistical computations" (p. 13). Specifically related to the graphs used in statistics, Graham (1987) categorized four purposes of using statistical visual information: (1) describing, (2) summarizing, (3) comparing and contrasting, and (4) generalizing and contrasting. All types of visual information can be assigned to these purposes. For instance, tables, bar graphs, line graphs, histograms, and stem-plots are usually used for the first, third, and fourth purposes. Boxplots are commonly used for summarizing data in addition to the third and the fourth purposes. Tables can also be used for organizing information before constructing graphs (Friel et al., 2001).

Since the selection and proper use of data representations are among the important aspects of statistical knowledge (Sorto, 2006) and a complete understanding of graphs should include recognizing which graphs to use for specific situations (Friel et al., 2001; Kosslyn, 2006), we assume that providing more purposes for visual information would facilitate a more comprehensive understanding of graphs. Tufte (1983) also paid attention to visual representations of statistics, and proposed:

> What is to be sought in designs for display of information is the clear portrayal of complexity. Not the complication of the simple; rather the task of the designer is to give visual access to the subtle and the difficult—that is, the revelation of complexity. (p. 191)

To reveal the complicated concepts of statistics with appropriate visual representations could be a purpose of referring to visual information. Unit 1 of the sample texts from the IPS referred to boxplots (see Figure 1) to show an example of boxplots. Unit 5 refers to a similar boxplot for the purpose of elaborating the information and comparing the data distributions of several variables presented in the boxplots. As a result, there are two different purposes of referring to visual information presented by the text when introducing the topic of boxplots.

We provide other analysis units from FSRE to show other possible purposes of referring to visual information in statistics texts. The following text is an excerpt from pages 53–54 (Coladarci et al., 2004).

> *As inspection of the box plots placed underneath the histograms confirms some of our earlier findings (see Figures 3.14c and d). As you see, we decided to present each box plot horizontally rather than vertically. (Recall from Section 3.8 that the small points extending beyond the ends of the whiskers signify extreme scores in the distribution. Do you see how these scores match up with the short bars in the tails of the histograms?) A comparison of the box lengths in Figures 3.14c and d indicates, as we found above, that mathematics scores are more bunched together (less spread out) than reading comprehension scores. In other words, the middle 50% of scores in the mathematics distribution lies within a smaller range (roughly between 670 and 700) than the middle 50% of scores in reading comprehension distribution (roughly between 655 and 705). These different patterns of variability suggest that test performance, at least for this group of juniors, varies more so in reading comprehension than in mathematics.*

In the excerpt, the authors referred to graphics reproduced in Figure 2 (Coladarci et al., 2004, p. 53, Figure 3.14) and elaborated on the information conveyed in the representations, with the purpose of comparing the two different types of visual presentation, histograms and boxplots, when displaying similar data. The visuals are referred to with the purpose of generalizing the information presented in the representations to make inferences about the problem context, as expressed in the last sentence. Hence, there are three purposes of referring to visuals presented in this sample text.

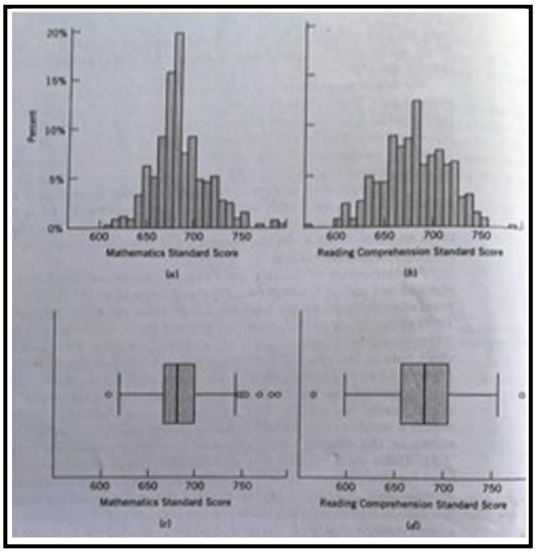

Figure 2. Comparison of histograms and boxplots (Coladarci et al., 2004, p. 53, Figure 3.14).

3.5. INTEGRATION OF VERBAL AND VISUAL INFORMATION

Two components of the attribute of the integration of verbal and visual information are the sequence of the verbal and visual information and verbal information provided together with visual information. The sequence of verbal and visual information concerns whether the visual display is placed before or after the verbal information, on the same or different pages. The verbal information provided with visual information may include captions, labels, and data scales.

Sequence of verbal and visual information. When reading statistics textbooks, a student might need to jump around and across pages to associate text with graphs. Placing the visual and related verbal information close to each other within the same visual field has been recommended as a technique for reducing cognitive load for comprehending text (Hegarty & Just, 1989; Mayer & Moreno, 2003; Shuard & Rothery, 1984).

The visual information referred to in Unit 1 of IPS, for example, is placed after the written information, while the visual information referred to in Unit 5 of IPS, which is similar to that referred to in Unit 1, is located before the written information, which is on a different page.

Verbal information presented together with visual information. The multimedia learning theory (Mayer & Moreno, 2003) suggests that integrated presentation, in which the text is placed within the graphic next to the elements it is describing, allows a reader to devote more cognitive capacity to essential processing. Accordingly, the verbal information provided in the statistical graphs, including labels or units of measure (Friel et al., 2001), may be useful clues for students when reading the visual information.

The written information provided in the visual referred to in Unit 1 of IPS (Figure 1) is the context of data, which is described in the caption. Also, some variable names are presented as abbreviations (i.e., Two hwy, Mini hwy) and data scales are presented on the axes. The verbal information provided in the visuals could help readers to comprehend the boxplot.

In summary, the five accessibility attributes of statistics text together with their supported literature are presented in Table 2.

Table 2. Components underlying the accessibility attributes of statistics texts and their significant literature

Attribute and the related components	Operational definition	Significant literature
Text concreteness:		
Linguistic meanings of statistical terms	The meanings of statistical terms related to natural and mathematical language.	Infrequently used words or words used with different meanings affect reading difficulty (Kaplan et al., 2009; Shuard & Rothery, 1984).
Learners' meanings of statistical terms	How the meanings of statistical terms relate to students' prior understanding are addressed in the text	It is helpful to make connections between students' prior understandings of the words and the specialized meanings in the text (Berenson, 1997).
Voice of statistics:		
Approach to statistical cognitions	Types of statistical cognitions used in presenting statistical terms.	The outcome of learning statistics should not be limited to understanding procedural concepts without grasping the underlying ideas (e.g., Franklin & Garfield, 2006; Garfield & Ben-Zvi, 2004). The different ideas arranged to introduce a statistical concept may be associated with types of statistical cognitions (Garfield & Franklin, 2011).
Approach to meanings of data	Types of meanings of data addressed in presenting statistical terms.	How the meanings of data addressed in statistics texts may associate with reasoning (Bakker & Gravemeijer, 2004; Konold et al., 2015; Pfannkuch, 2011) and conceptions of statistics (Idris & Yang, 2017).
Text coherence:		
Coherence of approaches to statistical cognitions	The connections of concepts and contexts regarding statistical cognitions.	The overall structure of a statistical concept can include its connection to other statistical concepts or statistical ideas, which should be pointed out when introducing the concept (Franklin & Garfield, 2006; Garfield & Ben-Zvi, 2004; Rossman et al., 2006).
Coherence of approaches to meanings of data	The connections of concepts and contexts regarding meanings of data.	Using similar data or data contexts to introduce different concepts could assist students to be able to extend the contexts and apply them in new situations and develop their understanding on the concepts (Garfield, 2003).
Selective use of visual information:		
Types of visual information	The type of visual information referred to when elaborating statistical terms.	Different types of graphs may have different effects on students' recognition of statistical concepts (Cooper & Shore, 2010) and graph processing (Vekiri, 2002).
Purpose of visual information	The purpose of the visual information referred to when elaborating statistical terms.	A complete understanding of graphs should include recognizing which graphs to use for specific purposes or situations (Friel et al., 2001; Kosslyn, 2006).
Integration of verbal and visual information:		
Sequence of verbal and visual information	The referred to visual display is before or after the verbal information within which statistical terms are elaborated.	Placing the visual and related verbal information close to each other within the same visual field has been recommended as a technique for reducing cognitive load for comprehending text (Hegarty & Just, 1993; Mayer & Moreno, 2003; Shuard & Rothery, 1984).
Verbal information presented with visual information	The verbal information provided as captions, labels, and data scales with the visual information.	The visual characteristics of graphs and information in the graphs can provide clues about the text to readers (Friel et al., 2001).

By applying the accessibility framework to the analysis of statistics textbooks, we are informed that the concept of boxplots, is introduced as basic knowledge followed by statistical reasoning. The two components of statistical cognitions and the three types of meanings of data utilized in presenting the concept of boxplots may provide an opportunity for readers to learn the concept rather than just the technical skills. In addition, since the concept of boxplots is interrelated to other corresponding statistical concepts, and similar data contexts to the previous concepts are used, it may indicate the coherence of the textbook in presenting the boxplots concept. It may help readers to understand the interrelated concepts and the big ideas in statistics.

The verbal information provided with the visual information, which included the data context in its caption, as well as the names of variables and data scales, may be helpful clues for readers in comprehending the texts related to the visual information. The weaknesses may appear in introducing the term of boxplots without relating it to learners' experience, and the data contexts used might be unfamiliar to our intended readers, Indonesian EFL pre-service teachers. Moreover, the absence of statistical thinking related to the concept of boxplots could hinder more advanced understanding of the concept.

4. POTENTIAL CONTRIBUTIONS OF THE FRAMEWORK

Although the accessibility framework is proposed for analysing a statistics textbook or for comparing two or more statistics textbooks at college level, the five attributes also have potential for the teaching and learning of college statistics courses. For instance, referring to the two components of the attribute of text concreteness, teachers can identify statistical terms having different meanings between statistics and natural language that may be ambiguous for students. Teachers may consider specific approaches, such as by exploiting the terms (Kaplan et al., 2014), to counteract students' misunderstanding of such terms.

Another potential teaching approach in college statistics course is reading, given that learning statistics through reading is associated with better performance when proper reading materials and supports are provided (Brisbin & Maranhao do Nascimento, 2019). Hence, the components of the accessibility framework could be taken as the basis for designing proper reading materials when reading is applied as a teaching pedagogy. For instance, by taking the two components under the attribute of integration of verbal and visual information, different versions of reading materials for introductory statistics classes can be designed and modified based on the sequence of verbal and visual information, as well as types of verbal information provided with the visual information (i.e., captions, labels, and data scales). The findings from such investigations could reveal not only which versions are associated with students' better comprehension, but also possible factors related to students' difficulties in learning statistics through reading.

In addition, taking the two components under the attribute of voice of statistics could reveal cognitive demands required by statistics tasks within textbooks. Using these components might result in a more comprehensive analysis than using levels of demands for mathematics tasks as used by Jones and Tarr (2007), considering the different characteristics between mathematics and statistics (Rossman et al., 2006).

Furthermore, further application of the framework on text analysis could involve the perspectives of textbook users. Some studies have focused on investigating perspectives of students and experts on the quality of statistics textbooks (Harwell et al., 1996; Nolan & Swart, 2015). The attributes and related components of the accessibility framework could be used to extend and deepen such studies to gain more comprehensive perspectives of textbook users.

Another potential of this framework is that it could be extended to the analysis of mathematics textbooks. For instance, when geometry is taken as the content to be analysed, the components for each accessibility attribute can be modified and elaborated by referring to the levels of geometric thinking (Van Hiele, 1986) and cognitive processes and reasoning in learning geometry (Duval, 1995, 1998).

On the other hand, in conceptualizing the attributes of the framework, we adapted the accessibility attributes of science texts (McTigue & Slough, 2010) and referred to the readability components of mathematics texts (Shuard & Rothery, 1984). Hence, this study contributes to both sets of literature. That is, we not only extend the accessibility attributes of science texts to statistics texts, but also strengthen the background theories for the attributes together with their essential components. We have also reconstructed and classified the components of readability of mathematics texts into the five accessibility attributes.

The accessibility framework can be used to analyse statistics textbooks as has been discussed in the previous section. Textbook analysis is rare in the statistics education literature, particularly at the college (tertiary) level, as we found very few relevant studies after searching online using keyword combinations such as "statistics", "textbook", "analysis" and "text analysis". The few studies in this area can be distinguished based on two different foci, that is, analysis based on textbook content (e.g., Cobb, 1987; Gea et al., 2017; Huberty & Barton, 1990) or based on the perspectives of textbook users (e.g., Harwell et al., 1996). Our framework focuses on text accessibility, which connects textbook content and textbook users.

Analysing college statistics textbooks by using the proposed accessibility framework can reveal not only how the content of statistics is presented in the textbooks, but also the comprehensibility of the textbooks for particular readers. That is, the attribute of text concreteness may indicate the comprehensibility related to the meanings of statistical terms, while text coherence may reveal the comprehensibility related to the interrelations of statistics concepts. It can be supplemental to the language analysis of textbooks using Halliday's functional framework (O'Keeffe & O'Donoghue, 2015) and can shed light on the educational design of college textbooks (cf. Golding, 2014).

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