A comparison of keystroke efficiency and accuracy of predicted text across three word prediction software applications

Brief Report

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Introduction

Assistive Technology (AT) refers to "any item, piece of equipment, or product system, whether acquired commercially, modified, or customized, that is used to increase, maintain, or improve functional capabilities of individuals with disabilities." (Individuals with Disability Education Act, 2004). The benefits associated with AT as it relates to increasing student performance and independence has been far reaching for individuals with physical and low incidence disabilities. According the National Assistive Technology Research Institute (NATRI), students with low-incidence disabilities are much more likely to use technology than students with learning disabilities (Hasselbring & Bausch, 2006). This inequity is problematic as there is literature suggesting that assistive and instructional technology can improve students' self-esteem, motivation, work efficiency, productivity, as well as avoid behavior problems (Cumming et al., 2008; Forgrave, 2002; Quenneville, 2001).

A variety of factors may contribute to the underuse of AT by these populations. First, research suggests that teachers report insufficient knowledge about how to integrate technology into general education curriculum (Bowser & Reed, 1995; Dalton & Roush, 2010; Michaels & McDermott, 2003). The effectiveness of technology is limited by the effectiveness of the instructional strategy embedded within the technology or implemented in conjunction with the tool. Poor instructional strategy can impact the perception of the effectiveness of the technology and subsequent use in the instructional environment. Next, students with learning disabilities and emotional/behavior disorders do not use assistive and instructional technology to its full potential (Evmenova & Behrmann, 2011). This phenomenon may result in mediocre results that do not provide reinforcement for the continued use by the student. Finally, Dalton and Roush (2010) suggest that a significant portion of the AT literature is not based on rigorous research methods. This lack of strong empirical support could result in reduced visibility in the field of education regarding increased outcomes when incorporating the use of AT for students with high incidence disabilities.

All students are entitled to the consideration of technology accommodations including students with high-incidence disabilities (Quinn et al., 2009). Evidence exists that technology can compensate for students with a variety of high incidence disabilities. More up-to-date-experimental research is needed to determine the true value of assistive and instructional technology for enhancing performance of students with learning disabilities and emotional/behavioral disorders (Fitzpatrick & Knowlton, 2009).

One technology that has shown promise for students with high incidence disabilities is Word Prediction. From predicting text as you type in a search engine field to the auto-completion of words when texting via a smart phone, word prediction is a digital writing support that has become mainstream. Word prediction operates as follows: (a) a student types the first letter of a word, (b) a numbered list of words appears based upon this initial keystroke, (c) the student presses the corresponding key if the intended word appears in the list and the word in inserted into the composition. If the intended word does not appear, the student types the second letter and the word list changes based upon this two-letter combination. As the student continues to type letters, the list of words is refined based upon each entry.

In educational settings, word prediction can be used in word processing applications to support writing outcomes. Though the research is limited, the data suggest the primary benefits of word prediction is improved spelling accuracy and an increase in keystroke efficiency for students with learning, physical, and developmental disabilities (Lewis et al., 1998, MacArthur, 1998; Tumlin & Heller, 2004). In addition to an increase in correctly spelled words, Mirenda and Turoldo (2006) reported that the use of word prediction resulted in a higher percentages of legible words and correct word sequences.

The difficulty in the field of AT, and word prediction in particular, is the ever advancing technological innovations. Due to this rapid progress, researchers are unable to maintain a similar pace evaluating empirically the performance of each technology in applied settings. As more and more school systems afford students the opportunity to utilize such technologies daily, it is difficult to identify which word prediction software application is most effective with targeted populations. Thus it is imperative that educators and consumers at large have software application performance information available to make an informed decision about the most accurate and efficient AT tool available for immediate use.

Purpose of the Study

In order to make an informed decision, data must be available to illustrate the overall effectiveness of word prediction software applications currently available. The purpose of this study is to evaluate the differential effects of three different word prediction applications on keystroke efficiency and accuracy of predicted text. Keystroke efficiency is defined as the relative difference in the number of key presses required to enter text in the word processing application when compared to the original student writing sample. Accuracy of predicted text is defined as the ability of the word prediction application to accurately display the word the student intended based on the student key presses.

Participants and Setting

Student writing samples were collected in a 6th grade inclusive Social Studies classroom at a middle school. The environment was structured similar to a state-wide assessment event. To evaluate the performance of the word prediction applications across a cross-section of student writing samples, 12 students between the ages of 11 and 13 years were randomly selected to participate in the study. The student populations included typically developing students, students with a learning disability, and students with emotional/behavior disorders (see table 1).

Table 1

Student Demographics

Student	Ethnicity	Gender	Disability category
Isaiah	African American	Male	EBD
Dwayne	Caucasian	Male	EBD/ADHD/Corrective Lenses
Morgan	Caucasian	Female	EBD/ADHD
Kelly	Caucasian	Female	EBD
Tyler	Caucasian	Male	Typical
Shelby	Caucasian	Female	Typical
Jarod	Caucasian	Male	Typical
Madison	Caucasian	Female	Typical
Elizabeth	Caucasian	Female	LD
Warren	Caucasian	Male	LD
Paul	Hispanic	Male	LD/ADD
Garrett	Caucasian	Male	LD

Note: EBD: emotional/behavior disorder; ADHD: attention deficit hyperactivity disorder; LD: learning disability; ADD: attention deficit disorder

Materials

Student writing materials. Each student received a hard copy of the writing prompt, two sheets of lined notebook paper, and a writing utensil.

On Demand Writing Prompt. The writing prompt was a released 6th grade state-wide assessment on-demand writing (ODW) prompt developed by NCS Pearson. NCS Pearson currently provides large-scale assessment services in 25 states and for the U.S. Department of Education. The selection of the writing prompt closely aligned with the content students were currently studying in their Social Studies class and contributed to their preparedness in taking the end of the year common core assessment.

Word Prediction Software. Three software applications were evaluated: Co:Writer, Read&Write GOLD, and WordQ (see table 2). Read&Write GOLD and WordQ software applications were free trials downloaded from the internet. The Co:Writer free trial installation disc was obtained by submitting a written request to the company representative. Each application was tested using the default settings. WordQ was the only application that required a selection of the word set to use and the advanced word set was selected. WordQ and Co:Writer displayed 5 words in the prediction window by default. Read&Write GOLD displayed 12 words in the prediction window by default. Following the initial data collection procedure using the default settings, Read&Write GOLD was set to display 5 words in the predictions window to identify performance variations.

Table 2

Word prediction software applications

Software	Feature set	Version	Installation type	Default # of words in prediction window
Read&Write GOLD	One of multiple tools	v. 11	Download	12
Co:Writer	Stand alone	v.6.0.2	Disc	5
WordQ	Stand alone	v.3.0.27	Download	5

Hardware. Two computers and one iPad 2 were used during the investigation. The computers were used to enter student writing compositions via each word prediction application and to collect inter-observer agreement data (see table 3). The iPad 2 was used to record the student reading the writing sample aloud as they followed along with their finger.

Table 3

Computer hardware specifications

Model	Processor	Memory	Operating system
Dell Latitude E6510	Intel Core i7 @2.67GHz	4 GB	Windows 7 Enterprise 32 bit
Lenova Thinkpad X201T	Intel Core i7 @2.13GHz	4 GB	Windows 7 Professional 64 bit

Research design

Each writing sample was entered into the word prediction applications by the researchers across sessions in accordance to a multi-element design. This research design allows for with-in subject and across-groups analysis. This particular design is a popular methodology in fields of study where you have smaller population sizes (e.g., special education) and is useful for identifying evidence-based practices (Horner et al., 2005). The order of student composition entry and order of applications used were randomly selected.

Procedures

Student writing samples. The writing prompt was read aloud to the entire class. Students were given the opportunity to seek clarification and adequate time to formulate their response. Once individual students had completed their response, they were asked to accompany the researcher to the hallway. Students then independently read their written response as the researcher recorded the video of the passage and the reader following along with his or her finger. Once the entire class had finished their responses, all materials were returned to the researcher and the writing session concluded.

Conversion to digital text. To identify the baseline number of keystrokes without word prediction, each students' handwritten composition was retyped by the researcher with no error correction.

Word prediction text entry. To identify the performance of each word prediction application, the researcher typed the text into a Microsoft Word document using the randomly assigned order of student composition entry and order of word prediction application use. To ensure that the entered text matched the intended text, a corrected passage was created using the student oral reading of the written passage.

Counting keystrokes and prediction as intended. To determine keystrokes required, every key press was manually counted as the text was entered. For example, if a word was capitalized, then the shift key press was counted as a key stroke in addition to the letter key press. When using word prediction, each letter press was counted in addition to the keystroke required to insert the predicted word into the text. If a word did not appear in the prediction window, the word was marked not predicted on the data sheet. The original text was then erased if spelled incorrectly. The correct word intended by the student was typed into the passage and the number of key presses was then counted.

Inter-Observer Agreement. To ensure data integrity, reliability data were collected on both keystroke efficiency and intended word prediction accuracy. The point-by-point method (i.e., number of agreements divided by agreements plus disagreements and multiplied by 100) was used to calculate the agreement of (a) number of keystrokes per word, and (b) accuracy of intended word for each word prediction software application. Reliability data on number of keystrokes per word indicated a mean of 97.8% agreement across software applications with a range of 96% to 100% agreement. A mean of 100% agreement was obtained for accuracy of intended word predicted across all software applications evaluated.

Findings

Keystroke efficiency. Table 4 shows the results for each word prediction application by population. The data indicate that across all populations Read&Write GOLD was the most efficient word prediction application with an average reduction of 59.6% key strokes (range, 57.3% to 62.6%), followed by Read&Write GOLD set to a 5 word window at 55.3% (range, 51.4% to 58.6%), WordQ at 48.5% (range, 46.0% to 52.1%), and Co:Writer at 45.5% (range, 42.8% to 47.1%). When considering the performance of the word prediction applications across individual populations, the pattern of keystroke efficiency remained the same with the exception of students with EBD. There was a slight key stroke reduction improvement for students with EBD when using Co:Writer (47.1%) as compared to using WordQ (46.1%).

Table 4

Average number of keystrokes and percentage reduction by student population

	Keystroke Count and % Reduction by Category								
	Not corrected in MS-Word	WordQ		Read&Write GOLD		Co:writer		Read&Write GOLD (5)	
	Keystrokes	Keystrokes	% change	Keystrokes	% change	Keystrokes	% change	Keystrokes	% change
EBD	448	242	46.1%	191	57.3%	237	47.1%	218	51.4%
LD	464	250	46.0%	196	57.8%	265	42.8%	210	54.8%
Typical	626	300	52.1%	234	62.6%	336	46.4%	259	58.6%
Overall	513	264	48.5%	207	59.6%	279	45.5%	229	55.3%

Note: Read&Write GOLD(5): the Read&Write GOLD word prediction application set to a 5 word window

When considering the performance of the word prediction applications, data were analyzed at the word level (see Table 5). During data collection, the letter press was recorded when the intended word appeared in the word prediction window. To calculate the percentage of letters of a word required to be typed to enter word in text, the number of key presses required for the intended word to appear was divided by the number of key presses required to enter the word into the text manually. For example, if a word required 2 key presses to appear in the prediction window and 4 key presses were necessary for manual entry into the text, then 50% of the word was required to be typed for insertion into the text.

Table 5 shows the percentage of the word required to be typed to enter word into the text. The data demonstrates that Co:Writer required the highest percentage of key presses per word (67.0%; range, 59.6% to 78.0%), followed by WordQ (63.1%; range, 56.0% to 785.2%), Read&Write GOLD set to a 5 word window (53.3%; range, 30.1% to 79.9%), and Read&Write GOLD (50.0%; range, 42.3% to 77.9%). Note that the data follow similar patterns for all students with the exception of Dwayne with Co:Writer (73.7%) being most efficient, followed by Read&Write GOLD (77.9%), Read&Write GOLD set to a 5 word window (79.9%), and WordQ (85.2%).

Table 5

Average percentage of letters of a word required to be typed to enter word in text

	Read&Write GOLD	WordQ	Co:Writer	Read&Write GOLD (5)
Dwayne	77.9%	85.2%	73.8%	79.9%
Isaiah	42.4%	58.2%	65.0%	49.2%
Kirsten	48.4%	61.0%	64.4%	55.5%
Morgan	46.3%	60.0%	64.9%	54.6%
Madison	48.2%	59.9%	67.2%	52.4%
Shelby	45.8%	58.4%	64.1%	52.5%
Tyler	45.2%	59.2%	67.3%	50.4%
Jared	42.3%	56.0%	59.6%	46.4%
Paul	45.7%	57.9%	67.9%	30.1%
Garrett	52.3%	65.3%	66.1%	56.3%
Elizabeth	50.4%	65.8%	65.2%	52.5%
Warren	55.2%	69.7%	78.0%	59.3%
Overall Average	50.0%	63.1%	67.0%	53.3%

Note: Read&Write GOLD(5): the Read&Write GOLD word prediction application set to a 5 word window

Prediction as intended. The prediction as intended data were similar across all word prediction applications (see Table 6). The data indicate that across all populations Read&Write GOLD set to a 5 word window was the most accurate word prediction application with an average unpredicted text of 3.3 words (range, 0 to 11), followed by Read&Write GOLD using default settings at 3.8 (range, 0 to 10), WordQ at 4.5 (range, 3 to 15), and Co:Writer at 9.5 (range, 3 to 22) When considering the performance of the prediction as intended applications across populations, the pattern of prediction efficiency remained the same.

Table 6

Number of words not predicted by word prediction application.

	total number of words in text	Read&Write GOLD	WordQ	Co:Writer	Read&Write GOLD (5)
Dwayne	39	10	15	8	11
Isaiah	62	0	2	0	0
Kirsten	171	2	5	11	2
Morgan	99	2	2	8	2
Madison	123	4	4	13	4
Shelby	76	1	1	7	1
Tyler	189	4	2	22	4
Jarod	94	3	5	11	3
Paul	102	2	5	12	2
Garrett	65	4	5	7	4
Elizabeth	132	3	6	12	5
Warren	58	2	2	3	2
Overall Average	101	3	5	10	3

Summary

Assistive technology is not fully utilized by students with high incidence disabilities for two main reasons. First, educators lack sufficient understanding of what devices should be selected and limited research is available on how the devices can positively impact this unique population of learners. The current study provides data to inform this decision making process. The data suggest that Read&Write GOLD with the default settings or with a 5 word window can reduce the number of keystrokes required while predicting the intended word with a greater efficiency as compared to Co:Writer and WordQ.

Limitations and Research Implications

One significant limitation to the study is that students did not independently manipulate the software applications being studied. Though this was intentional to control for implementation fidelity, follow-up research is necessary to identify to what degree learners can be taught to use word prediction software and subsequent writing outcomes. Additionally, it would be worthwhile to seek student opinions pertaining to which software application they perceive to assist them the most and how they believe it positively impacts their overall performance. Finally, additional research is warranted to expand and extend the effectiveness of word prediction software applications across content areas and grade levels.

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