A Controlled Evaluation of Computer- versus Human-assisted Oral Reading

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Abstract. A year-long study of 144 second and third graders compared outcomes (gains in test scores) and process variables (e.g. words read) for Project LISTEN's Reading Tutor, human tutors, and a classroom control. Human tutors beat the Reading Tutor only in word attack. Both beat the control in grade 3 word comprehension.

1. Experimental Design

Project LISTEN's Reading Tutor listens to children read aloud and helps them [1], and also lets them write and narrate stories [2]. In 1999-2000, to "prove and improve" the Reading Tutor – to evaluate against conventional instruction, and identify areas for improvement – we compared it to one-on-one human tutoring, and to spending the same time in class.

  Students. Students were 144 second and third graders (ages 7-10) at an urban elementary school near Pittsburgh, Pennsylvania, that had not previously used the Reading Tutor. Teachers in 12 classrooms each chose their 12 poorest readers, based on a finding that the 1998 Reading Tutor seemed to make a bigger difference for students in the bottom half [3].

  Treatments. We assigned each student to the same treatment 20 minutes daily for the year. Each day included 60-70 minutes of reading instruction plus varying time on related activities. Thus all students in a given classroom received mostly the same instruction, with tutored students averaging 0 to 15 minutes more time per day on reading and writing. Teachers rotated scheduling to vary which subjects students missed while being tutored.

  Control. Regular instruction used a basal reading curriculum, with class size about 24.

  Reading Tutor. Children took turns throughout the school day using one Reading Tutor computer in their classroom. Teacher cooperation was essential to this arrangement, so the principal chose six classrooms to get Reading Tutors based on his estimate of teachers' willingness to cooperate – possibly a confound, but necessary. Moreover, according to the principal, all classroom teachers in the study were comparably experienced veteran teachers.

  Human tutoring. Variables in tutoring include *personnel*, *setting*, *activities*, and *materials*.

   Personnel: The human tutors were certified elementary teachers already employed by the school. Studies of one-on-one tutoring in elementary reading have employed tutors with varying degrees of training, from volunteers [4] to paraprofessional teachers' aides to certified teachers to certified teachers with specialized training in a particular reading program. Using certified teachers rather than paraprofessionals has been associated with positive results for one-on-one reading tutoring [5]. The tutors in our study had at least a bachelor's degree in elementary education and 0-2 years experience teaching (often preschool children), but no specialized training in reading tutoring. Thus we expected them

to do better than classroom instruction, but not as well as the world's best tutor – an unrealistic comparison even for a research study, let alone for large-scale implementation.

Setting: Each tutor tutored 6 students from one class, one at a time at a desk in the hall.

Activities: Tutors helped students read and write, and logged each session's activities.

Materials: To control for materials, we asked human tutors to use bound copies of the same stories used in the Reading Tutor, to refrain from bringing in outside books, and to limit any writing (by student or tutor) to student journals we designed for that purpose.

Assignment of students to treatments. We initially assigned 60 students to use the Reading Tutor, 36 students to human tutors, and 48 students to the control condition. To keep either type of tutoring from influencing the other, each classroom had only one type.

Ten students was the maximum we thought could share one Reading Tutor. Two teachers tried to add 1-2 more students, but could not always get them on. We excluded these 3 "part-timers" from analysis. Other students in each Reading Tutor room were in-room controls.

Similarly, 6 students was the most each human tutor could cover, given her other duties. The other 6 students in the same room served as in-room controls, likewise chosen so as to make treatment groups statistically well-matched. 131 of 144 students completed the study.

Outcome measures. The Woodcock Reading Mastery Test (WRMT) [6] is an individually administered test normed by month within grade, so that a pre- to post-test gain of 0 means the student stayed at the same percentile relative to peers. WRMT subtests measure different reading skills with mean 100 and standard deviation 15. Trained testers pre-tested students in September 1999 and post-tested them in May 2000, using four WRMT subtests: Word Attack (WA) for decoding skills, Word Identification (WI) for reading single words, Word Comprehension (WC) for word meaning, and Passage Comprehension (PC) for understanding text. The testers also measured students' independent oral reading fluency as the median number of words read correctly in one minute for three grade-level passages.

2. Results

We found surprisingly few differences among treatments. We expected the human tutors to lead across the board. Instead, as Table 1 shows, human tutoring significantly outgained the Reading Tutor only in Word Attack. Human and computer tutoring both surpassed the control in grade 3 Word Comprehension gains. No other differences were significant. In grade 3 Passage Comprehension, a trend favored the Reading Tutor over the control. The absence of significant differences in fluency gains is especially surprising, because fluency is such a sensitive measure of growth [7]. A few differences among tutors were significant [8].

Table 2 compares Reading Tutor and human tutor process variables, using comprehensive records at multiple levels of detail, plus hand-coded videotapes of 49 sample sessions.

Table 1: Comparison of treatment groups' pretest scores and gains on each test, by grade

Subtest	Pretest Score			Gains			ANOVA covariates	Main Effects	Contrast Effect
Grade 2:	CTRL n=19	RT n=29	HT n=17	CTRL	RT	HT	(pretests)	p	Size
Word Attack (normed)	86.6	84.6	83.3	8.2	3.1 <?	11.0	WI, WA	0.07	**0.58**
Word ID (normed)	90.2	90.3	89.3	1.6	-0.7	1.0	WI, WC	0.16	
Word Comp (normed)	89.7	88.4	90.4	5.6	4.4	4.4	WI, WC	0.73	
Passage Comp (normed)	90.8	88.9	89.5	1.9	2.3	2.0	WC, PC	0.90	
Fluency (WPM)	12.9	12.9	15.4	39.1	34.8	40.7	FLU	0.67	
Grade 3:	n=20	n=29	n=17						
Word Attack (normed)	93.4	95.3	93.7	-1.1	-2.8 <?	3.6	WI, WA	0.10	**0.65**
Word ID (normed)	90.1	90.3	91.3	0.3	1.8	1.8	WI, WC	0.53	
Word Comp (normed)	89.7	90.4	94.3	0.7 <<	4.3	3.4	WI, WC	0.02	**0.56**
Passage Comp (normed)	89.2	89.5	90.9	1.0 <?	4.8	4.1	WC, PC	0.14	**0.48**
Fluency (WPM)	42.0	37.7	41.8	19.9	20.5	28.1	FLU	0.18	

Table 2: Comparison of process variables for Reading Tutor (RT) and human tutoring (HT), by grade

Process variable, data source (and how derived) [averaged by student or per videotaped session; shown by grade and by RT room or HT initials]	Grade 2		Grade 3	
	Reading Tutor n=29	**Human tutor** n=17	**Reading Tutor** n=29	**Human tutor** n=17
Total number of sessions RT event database (days with any events) HT log (days with any logged activity)	**67 days** 90 RT201 54 RT211 56 RT212	**73 days** 67 AC 77 MB 77 ME	**71 days** 70 RT301 57 RT303 86 RT304	**>>61 days** 61 LN 62 MM 58 NJ
Reading/total time in videotapes (hand-coded; other time included writing, waiting for RT, etc.)	**11/20 min.**	**11/18 min.**	**9/20 min.**	**7/15 min.**
Story words seen per session RT portfolio (#words of finished stories only!) HT log (#words in logged stories; prorated for never-finished stories based on # pages read)	**122 words** 120 RT201 108 RT211 135 RT212	**<? 154 words** 112 AC 224 MB 120 ME	**143 words** 122 RT301 143 RT303 162 RT304	**<< 262 words** 258 LN 313 MM 194 NJ
Level of stories finished, chosen (tutor/child) RT portfolio (shows if finished and who chose; finished stories averaged a half level lower.) HT log (shows level, pages read, not who chose)	**1.1(1.8/1.1)** 1.1 RT201 0.8 RT211 1.2 RT212	**<< 1.8** 1.4 AC 2.8 MB 1.2 ME	**1.7(2.5/1.8)** 1.4 RT301 2.0 RT303 1.7 RT304	**<< 2.2** 2.3 LN 2.2 MM 2.2 NJ
Percentage of rereading RT portfolio (% of finished stories read before) HT log (% of finished stories read before)	**30%** 34% RT201 28% RT211 29% RT212	**>> 19%** 24% AC 11% MB 21% ME	**24%** 25% RT301 18% RT303 30% RT304	**>> 13%** 13% LN 18% MM 6% NJ
Percent of sessions with any writing activity RT event logs (% of days with edit events) HT log (listed writing activities)	**38%** 46% RT201 37% RT211 32% RT212	**<< 64%** 85% AC 37% MB 70% ME	**28%** 36% RT301 25% RT303 22% RT304	**<< 58%** 67% LN 60% MM 44% NJ

Control. A questionnaire asked each teacher how much time her class spent on reading.

Reading Tutor. The Reading Tutor recorded student utterances, speech recognizer output, a detailed event log, a more selective event database for runtime reference, student portfolios listing stories read and new words seen, and counts of distinct words and stories read.

Human tutoring. We analyzed tutors' session logs, and archived students' writing journals. This diverse data may help us explain outcome differences and improve the Reading Tutor.

References (see also www.cs.cmu.edu/~listen)

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