Comparing graphs and text: Effects of complexity and task

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Graphs are commonly believed to facilitate users' comprehension. We explored the effect of graphs on comprehension compared to text, manipulating content complexity (single bar vs. double bar graphs) and question type (point-locating vs. comparison questions). A total 78 college students viewed graph and text stimuli and answered comprehension questions while their eye movements were recorded. The results indicate that students do not always process graphs more efficiently than text conveying the same information. Students processed graphs significantly faster than text only when the more complex questions were shown. When the more complex graphic patterns were presented, the advantage of graphs over text became less apparent. The students also spent the majority of their time looking at specific information on the axes and label regions of the graphs with the increasing complexity of graphs and tasks. These findings are discussed related to theories of learning including cognitive load theory and perceptual salience theory.

Keywords: Graph comprehension, text comprehension, task complexity, eye tracking

Introduction

When describing textual and diagrammatic representations of information, Simon (1978) and Larkin and Herbert (1987) distinguished between informational and computational equivalence of representations. Two forms of representations are *informationally* equivalent if information in one form is also derived from the other. On the other hand, two forms of representation are *computationally* equivalent if they are not only informationally equivalent but also inferences from each can be drawn quickly and easily. Diagrams are commonly considered to be computationally more efficient than text. However, this is not always the case when individual variables such as complexity are investigated (Freedman & Shah, 2002; Huang, Hong, & Eades, 2006; Roth & Bowen, 2003). This study was designed to increase our understanding of efficiency of graph processing when compared to text that is informationally equivalent.

Graphs have been used widely to communicate information in both academic and nonacademic settings. Understanding graph processing is an important goal for educators, cognitive scientists, and graphic designers because graph generation and comprehension is a fundamental part of curricula across various disciplines including literacy, science, and mathematics (Kramarski, 2004; Organisation for Economic Co-Operation and Development (OECD), 2000). When learning how to interpret and use graphs, students need to process various types of information simultaneously. For example, when taught to interpret Cartesian *x-y* coordinates, they learn to interconnect numerical data in the axes and transform numerical data to abstract entities (e.g., bars or lines) (Leinhardt, Zaslavsky, & Stein, 1990). From a cognitive perspective, Carpenter and Shah (1998) described graph processing as a function of interaction between the conceptual process of interpreting verbal sources (e.g., labels) and perceptual process of interpreting visual sources (e.g., bars, lines). Accordingly, understanding how graph viewers comprehend graphs has the potential of informing us to understand more precisely aspects of human information processing. In addition, a deeper understanding of graph processing is likely to be attributed to the design of more effective graphical representations (Peebles & Cheng, 2003).

Cognitive load theory, a widely accepted model of human information processing, rests on the assumption that cognitive capacity in working memory is limited, so that cognitive processing involving learning is executed under the constrains of limited working memory capacity (Sweller, 1988). Research associated with cognitive load suggests that effective instructional material promotes learning by allocating cognitive resources to activities that are relevant to learning and preventing cognitive overload that results in a lower performance (Clark, Nguyen, Sweller, & Baddeley, 2006; Plass, Homer, & Hayward, 2009; Sweller, Ayres, & Kalyuga, 2011). Cognitive load theory describes three types of cognitive loads; intrinsic, extrinsic, and germane loads (De Jong, 2010). Intrinsic load refers to the inherent characteristics of material itself and posits that some materials place high demands on cognitive process than others. Extrinsic load is unnecessary cognitive load that is imposed by poor material layout, surplus of information, etc. Finally, germane load refers to individual's factors involved in the process of learning such as interpreting, exemplifying, and organizing when dealing with intrinsic load. Our study focuses on the intrinsic cognitive load. Particularly, we are manipulating complexity of materials (i.e., graphs) by which the number of elements in the graphs that must be processed in working memory differs in order to investigate how the manipulation affects participants' information processing.

Two types of complexity are particularly salient to understand graphing: form (or content) complexity (Holzinger, Kickmeier-Rust, & Albert, 2008; Sweller & Chandler, 1994) and task complexity (Huang et al., 2006). Form complexity refers to the numbers of content components that need to be processed simultaneously in working memory for solving a problem (Elliott, Beddow, & Frey, 2009; Sweller & Chandler, 1994). An example of manipulating form complexity is the use of one as compared to two or more bars on a bar graph for displaying graphed information. Task complexity refers to the load imposed by task demands (Huang et al., 2006). An example of task complexity is use of questions that require locating a single point on a graph versus questions that require locating and comparing two or three points on a graph (Friel, Curcio, & Bright, 2001 for reviews).

Eye-tracking measures are well suited for studying printing representation such as graphs and words because they allow for direct process-related measures such as location and speed (de Koning, Tabbers, Rikers, & Paas, 2010; Körner, 2011; Peebles & Cheng, 2003). More specifically, eye tracking measures yield quantitative and qualitative data on specific regions of printed symbols, allowing a direct comparison of the average time spent on each are during comprehension (Körner, Höfler, Tröbinger, & Gilchrist, 2014; Lohse, 1997). Carpenter and Shah (1998) divided line graphs into five regions, x-axis, y-axis, pattern, labels, and titles, to examine the pattern of eye gazes of college students when reading the line graphs. They found that graph viewers identify values in the axes and labels (verbal interpretation processes), encode visual data in lines (pattern recognition processes), and integrate the two sources of information into a coherent interpretation. Similarly, when constructing their model of graph-based reasoning, Peeble and Cheng (2003) divided line graphs into x-axis, y-axis, graph pattern, question, and answer regions and measured the eye movement pattern of college students. The students scanned question elements, viewed the relevant regions (i.e., axes or pattern) in the target graph, and then answered the question. Based on the eye tracking data, Peeble and Cheng described search procedures and visual attention processes of graph viewers in graphing. Finally, Kim, Lombardino, Cowles, and Altmann (2014) used eye-tracking methods to investigate how subject characteristics of college students (e.g., reading ability) affected viewing time on graph subregions (e.g., x-and y- axes, graphic pattern, legend). Students with reading disabilities were significantly slower in processing linguistic regions than their peers with typical reading skills.

Examining the details of eye fixations and movements in graphs, we intended to expand this line of research theoretically and methodologically. Existing graph studies have provided valuable insights into variables involved in the graph viewer's cognitive processing. In our study, by comparing students' interactions with literate information presented in graphic and in text formats, we strove to better understand how elementary level of information comprehension is affected by variations in graphic and question types. We believe this information will lead eventually to guiding instructors and designers to develop instructional materials that provide optimal learning environments for typical and challenged learners. Methodologically, we would explore a new data measure to the eye-tracking stream in graph comprehension. We examine students' scanning patterns using entropy H value of eye transition data, derived from infor-

mation theory, which is suitable for generating natural results that are interpretable (Shic, Chawarska, Bradshaw, & Scassellati, 2008). We divide the graph displays into five regions (*x*-axis, *y*-axis, graphic pattern, legend, and question) for eye data analysis. As mentioned above, this approach is routinely used in graph studies (e.g., Carpenter & Shah, 1998; Peebles & Cheng, 2003); however, in the studies, mainly eye fixation data (e.g., viewing time) are reported. In our study, in addition to the eye fixation data, eye movement data including entropy H value and location of the first fixation were analyzed.

This study was motivated by our interest how eye tracking patterns might help us to better understand the effects of varying forms of information representation on students. Our primary aim was to explore how college students process informationally equivalent forms presented in two different modalities (i.e., text and graph). Our second aim was to develop more precise characterization of graph comprehension that vary in graphic form complexity and task type. For this second aim, we examined eye fixations (i.e., total gaze duration and total fixation counts) and eye movements (i.e., start locations participants were looking at first and eye transition analysis using entropy H) in individual areas of interest (AOIs: legend, pattern, *x*-axis, *y*-axis, and question).

Methods

Participants

We recruited participants from a psychology subject pool at the University of Central Arkansas. Subjects chose to be compensated in one of two ways. Some chose to receive extra course credit and other chose the compensation fee of $10/hour. All participants were native speakers of American English and showed negative histories for pervasive cognitive deficits, behavioral disturbances, neurological illness, psychiatric illness, hearing impairment, or uncorrected visual impairment including color-blindness[i]. This study was approved by the University's Human Subject Institutional Review Board (IRB) and all IRB policies were followed.

Eighty students agreed to participate in this study. Two participants were excluded from the analysis; data

for one subject had to be eliminated due to technical difficulties and another subject scored below one standard deviation (i.e., < 85) on a standardized intellectual test, Woodcock-Johnson III Test of Cognitive Abilities (Woodcock, McGrew, & Mather, 2002). The final cohort of subjects was composed of 78 college students (57 women; 21 men; mean age = 21.30, SD = 4.78).

Experimental stimuli

Stimuli included a total of 48 computer screens. We manipulated three variables, presentation modality (graph or text), question type (point-locating or comparison), and form complexity (single or double). Hence, eight presentation conditions were composed of a total 48 items (six items for each condition). The eight presentation examples are shown in appendix 1.
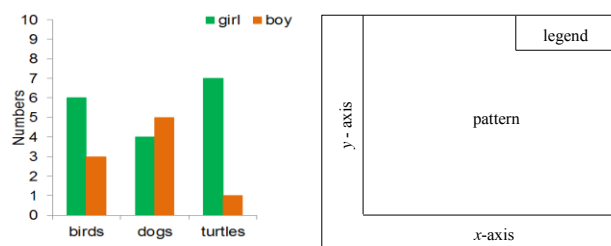

Figure 1. A sample graph with four areas of interest (pattern, legend, x-axis, y-axis) defined for the eye-tracking analysis. The areas were defined identically for all graphs.

The graph stimuli were adapted from a previous study of graph comprehension (Kim et al., 2014). Graphs were created to be simple and to avoid the use of content-specific knowledge. To study eye gaze positions, each graph was divided into four quadrants: (1) an *x*-axis consisting of three common objects (e.g., dogs, turtles, birds), (2) a *y*-axis with numbers ranging from 0 to 10, (3) graphic pattern (i.e., bars), and (4) a legend identifying referents represented in the graph (i.e., boy, girl). The location of these components on the graph stimuli is shown in Figure 1.

For the text stimuli, all sentences contained a subject (boy or girl), three common animate objects (e.g., dogs, turtles, birds) and identical sentence structures (e.g., The boy has two birds, three dogs, and seven turtles). In the single form condition, a ten-word sentence was presented on the screen (e.g., The boy has five dogs, two turtles, and one bird). In the double form condition, two double-spaced ten-word sentences were presented together on the

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[i] Our experiment used colors in the graph stimuli (e.g., bars in graphs). See Appendix 1.

screen (e.g., The girl has one turtle, five dogs, and two birds. The boy has three turtles, five dogs, and nine birds.).

For manipulating the form complexity, two graphic pattern conditions (i.e., single bar graph vs. double bar graph) in the graph stimuli and two text conditions (i.e., single sentence text vs. double sentence text) in the text stimuli were used. For manipulating the task complexity (question type), a point-locating question (e.g., How many dogs does the boy have?) and a comparison question (e.g., Does the girl have more turtles than birds?) accompanied graph or text stimuli. To minimize the potential memory constraints, the question was included on each of the stimulus screen rather than appearing separately. Appendix 1 shows examples of four graph types (i.e., a *single* bar graph with a *point-locating* question, a *single* bar graph with a *comparison* question, a *double* bar graph with a *point-locating* question, and a *double* bar graph with a *comparison* question) and four text types (i.e., *single* sentence text with a *point-locating* question, *single* sentence text with a *comparison* question, *double* sentence text with a *point-locating* question, and *double* sentence text with a *comparison* question) that were viewed by participants.

All 48 stimuli were presented to subjects individually on a computerized screen in a pseudo-randomized order. Participants did not view stimuli from the same condition on more than three consecutive trials. To avoid unintended effects of item order, we assigned the order of graphs to two sets, A and B, and alternated which set was presented to participants such that set A was presented for half of participants ($n = 39$) and set B ($n = 39$) for the other half[ii].

Eye-tracking apparatus

Eye movements were tracked using an LC Technologies head-free EyeFollower binocular system operating at 120 Hz. Gaze point tracking accuracy reported by the manufacturer is less than 0.4˚ throughout the operational head range (rater range: 30 inches and vertical range: 16 inches. Fixations ere extracted with a temporal threshold of 100 ms[iii] and a spatial dispersion threshold of 1.5˚ (minimum deviation of 25 screen pixels). Participants sat at a distance of 23.62 inches (60 cm) from the LCD monitor and used a custom-designed keyboard for inputting manual responses. Graphs were presented in a black component (e.g., *x*-axis, *y*-axis, letters) and two color components (i.e., bars) on a white background on a 24 inch (61cm) light-emitting diode (LED) monitor with a resolution of 1920 × 1080 pixels. The text and questions were presented in black Arial 20 point font. . The graphs subtended a horizontal visual angle of 9.6˚ and a vertical visual angle of 8.4˚. The characters for text and questions subtended a horizontal visual angle of 0.37˚ and a vertical visual angle of 0.46˚. Calibrations for fixations were accepted if fixation accuracy showed an average drifting error no greater than a quarter of an inch. The average root mean square error was 0.17 inches. Minds Eyetracking Solutions software program was used to analyze participants' fixation data.

Procedure

Participants individually completed all tasks in the following order: (1) general background questionnaire, (2) brief intelligence assessment, and (3) experimental eye tracking task. The entire procedure took approximately 40 minutes. Prior to the experimental task, the experimenters explained the eye-tracking methodology and participants were given time to become familiar with the equipment. This was followed by a thirteen-point calibration procedure and a practice trial on eight items to familiarize subjects with the stimuli and task. The experimenter provided verbal feedback regarding accuracy of answers for the practice items only.

[ii] To confirm that there was no significant difference between sets A and B, we compared participant data between the sets. Participants in sets A and B did not differ for age (set A $M = 20.21$, $SD = 2.15$, set B $M = 22.33$, $SD = 6.21$; $F(1, 76) = 4.07$, $p = .05$), graph response accuracy (set A $M = 47.39$, $SD = 0.74$, set B $M = 47.43$, $SD = 0.64$; $F(1, 76) = 0.11$, $p = .75$), text viewing time (set A $M = 5.76$ s, SD = 1.44, set B $M = 5.78$ s, SD = 1.19; $F(1, 76) = 0.01$, $p = .95$), or graph viewing time (set A $M = 5.29$ s, SD = 1.24, set B $M = 5.14$ s, SD = 1.13; $F(1, 76) = 0.29$, $p = .59$).

[iii] 100 ms is shorter than average fixation times reported in some previous studies as the minimal duration of a fixation (275 ms in Rayner, 1998). On the other hand, some researchers include gazes with fixation duration shorter than this values for text-graph co-reference stimuli. For example, Underwood, Jebbett, and Robert (2004) included gaze with a fixation duration above 60 ms for their sentence-picture verification experiments. Acarturk, Habel, Cagiltay, and Alacam (Acartürk, Habel, Cagiltay, & Alacam, 2008) included gaze above 100 ms for their graph-text comprehension experiments. Because these previous studies had most similar types of stimuli, we decided to include gazes above 100 ms in the analysis.

For the experimental trials, the experimenter instructed participants to view the stimulus and answer the accompanying question as rapidly and as accurately as possible; however, no time limit was given. To avoid a possible bias related to a left- and right- hand dominance, the experimenter asked participants to press the spacebar with their dominant hand. The participants controlled the timing of the presentation for each stimulus by pressing the spacebar to advance the program to the next trial after completing a trial. Each participant response to a comprehension question received a score of either 1 (correct answer) or 0 (incorrect answer). The maximum total score was 48 across all trials.

Results

Data were analyzed using SPSS version 17.0 for Windows (SPSS Inc., 2008). Incorrect responses (0.9 %) were excluded from the data analysis. For eye tracking data, the experimenter (1st author) visually inspected each trial to check that the tracker had correctly recorded eye movements. Approximately 4% of data were excluded due to track loss or program error. For the first research question, which addressed the effect of presentation modality on speed of subjects' comprehension processing, total gaze duration data were compared for 24 graph and 24 text stimuli. For the second question, which addressed subjects' eye fixation time for specific graphic subregions, total gaze duration and total fixation count data were compared for the four subregions (x-axis, y-axis, graph legend, and graphic pattern) for 24 graphs. For the third question, which addressed the effect of question type and graphic form complexity on the subjects' eye movements for graphic subregions, both location (i.e., first location subjects were looking at) and transition (Entropy *H*) analyses were used for four graphs from each condition (i.e., *single* bar graph with a *point-locating* question, *single* bar graph with a *comparison* question, *double* bar graph with a *point-locating* question, *double* bar graph with a *comparison* question).

Total gaze duration analysis for graphs and text

Total gaze duration (sum of the durations of fixations on graph or text stimuli) was calculated to address how presentation modality (graph vs. text) affected participants' processing speed when question type and form complexity were manipulated. Questions were presented with the graph or text stimuli on the screen; however, the duration of fixations on the question region was not included in the total gaze duration on graph or text stimuli. Table 1 shows the mean total gaze duration for graph and text stimuli across question type (point-locating and comparison questions) and form complexity (single and double). Total gaze duration was analyzed using a 2 (presentation modality: text, graph) × 2 (question type: point-locating, comparison) × 2 (form complexity: single, double) repeated measures analysis of variance (ANOVA) with Bonferroni-corrected post-hoc tests.

The ANOVA yielded three main effects and two 2-way interaction effects (see Table 2). Significant main effects were found for all variables (i.e., presentation modality, question type, and form complexity). First, the total gaze duration was significantly longer for text stimuli (M = 3351.0 ms) than for graph stimuli (M = 2839.7 ms). Second, the total gaze duration was significantly longer in the comparison question condition (M = 3542.6 ms) than in the point-locating question condition (M = 2647.1 ms). Third, the total gaze duration was significantly longer in the double form condition (M = 3542.5 ms) than in the single form condition (M = 2647.2 ms).

The first significant two-way interaction was found between presentation modality and question type. Post hoc Bonferroni test ($p < .05$) showed that the total gaze duration for graph and text stimuli did not significantly differ in the point-locating question condition, $t(77) = -1.46$, $p = .15$. Conversely, the total gaze duration was significantly shorter for graph stimuli than for text stimuli in the comparison question condition, $t(77) = -11.25$, $p < .001$. Second, presentation modality and form complexity significantly interacted. In the single form condition, the total gaze duration was significantly shorter for the graph stimuli than for the text stimuli, $t(77) = -14.86$, $p < .001$. However, in the double form condition, the total gaze duration between the graph and text stimuli did not significantly differ, $t(77) = -0.55$, $p = .59$.

Table 1. Means and standard deviation of total gaze duration (in ms) for graph and text stimuli across question type (point-locating and comparison question) and form complexity (single form and double form).

	Graph					Text				
	Point-locating Question		Comparison question			Point-locating Question		Comparison Question	
	Single	Double	Single	Double		Single	Double	Single	Double
Graph region	1924.4 (469.2)	3253.1 (683.9)	2298.9 (744.1)	3879.8 (978.9)	Text region	2544.8 (892.1)	2866.0 (1013.6)	3820.9 (1067.9)	4171.3 (1177.2)
Question region	1708.3 (689.1)	1998.8 (739.4)	2795.1 (901.8)	3044.1 (304.4)	Question region	1689.9 (546.0)	1938.9 (601.1)	2914.6 (966.9)	3178.7 (1031.7)

Note. Standard deviations are given in parenthesis

Table 2. Three-way repeated analysis of variance on total gaze duration by a function of presentation modality, question type, and form complexity.

		Total gaze duration				
	Source	MS	df	F	p	η^2_p
Main effects	Presentation modality (graph vs. text)	40.84	1	59.96	<.001	.44
	Error (Presentation modality)	0.68	77			
	Question type (point-locating vs. comparison)	125.14	1	212.74	<.001	.73
	Error (Question type)	0.59	77			
	Form complexity (single form vs. double form)	125.04	1	354.27	<.001	.82
	Error (form complexity)	0.35	77			
Two-way interaction	Presentation modality × question type	24.35	1	57.96	<.001	.43
	Error (Presentation modality × question type)	0.42	77			
	Presentation modality × form complexity	48.84	1	154.24	<.001	.67
	Error (Presentation modality × form complexity)	0.32	77			
	Question type × form complexity	0.77	1	3.12	.081	.04
	Error (Question type × form complexity)	0.25	77			
Three-way interaction	Presentation modality × question type × form complexity	0.49	1	2.53	.116	.03
	Error (Presentation modality × question type × form complexity)	0.19	77			

Note. Total gaze duration analysis was conducted based on the total gaze time in the graph and text regions (question region was not included in the analysis); significant at the $p < .05$ level

Table 3. Means and standard deviation of total gaze duration (in ms) and total fixation count for four areas of interest of graphs across question type (point-locating and comparison question) and form complexity (single and double).

	Total gaze duration				Total fixation count			
	Point-locating Question		Comparison Question		Point-locating Question		Comparison Question	
	Single	Double	Single	Double	Single	Double	Single	Double
Legend	280.92 (161.68)	675.88 (316.00)	268.77 (180.99)	734.66 (309.38)	1.21 (0.60)	2.22 (0.89)	1.09 (0.58)	2.27 (0.83)
Pattern	741.98 (251.68)	1318.67 (446.24)	756.61 (376.59)	1427.89 (505.70)	3.37 (1.26)	6.12 (2.31)	3.91 (1.76)	6.83 (2.43)
X-axis	734.30 (231.95)	903.13 (275.04)	1263.07 (438.05)	1578.58 (479.45)	3.41 (0.91)	3.80 (0.99)	5.34 (1.53)	6.34 (1.69)
Y-axis	400.00 (190.89)	464.52 (176.29)	268.92 (275.59)	229.32 (276.77)	1.23 (0.50)	1.41 (0.66)	1.03 (0.91)	0.91 (0.90)

Note. Standard deviations are given in parenthesis

Table 4. Repeated analysis of variance on total gaze duration and total fixation count for four areas of interest of graph across question type and form complexity.

	Factor	Total gaze duration					Total fixation count				
		MS	*df*	*F*	*P*	η^2_p	*MS*	*df*	*F*	*p*	η^2_p
Legend	Question type[a]	0.04	1	2.26	.14	.03	0.08	1	0.43	.51	.01
	Error	0.02	77				0.19	77			
	Form complexity[b]	14.45	1	303.26	<.001	.80	92.73	1	220.76	<.001	.74
	Error	0.05	77				0.42	77			
	Question type × form complexity	0.10	1	3.93	.05	.05	0.49	1	2.12	.15	.03
	Error	0.03	77				0.23	77			
Pattern	Question type	0.30	1	2.59	.11	.03	30.63	1	20.24	<.001	.21
	Error	0.12	77				1.51	77			
	Form complexity	30.37	1	374.24	<.001	.83	628.16	1	357.55	<.001	.82
	Error	0.08	77				1.76	77			
	Question type × form complexity	0.17	1	4.62	.03	.06	0.61	1	0.84	0.36	.01
	Error	0.04	77				0.72	77			
X-axis	Question type	28.28	1	256.44	<.001	.77	390.66	1	277.93	<.001	.78
	Error	0.11	77				1.41	77			
	Form complexity	4.57	1	113.09	<.001	.60	37.69	1	60.26	<.001	.44
	Error	0.04	77				0.63	77			
	Question type × form complexity	0.42	1	10.27	.002	.12	7.14	1	11.73	.001	.13
	Error	0.04	77				0.61	77			
Y-axis	Question type	2.62	1	49.62	<.001	.39	9.53	1	15.66	<.001	.17
	Error	0.05	77				0.61	77			
	Form complexity	0.01	1	0.38	.54	.01	0.06	1	0.14	.71	.01
	Error	0.03	77				0.41	77			
	Question type × form complexity	.21	1	5.84	.02	.07	1.82	1	4.07	.04	.05
	Error	0.04	77				0.45	77			

Note. [a] *Point-locating question vs. comparison question;* [b] *single bar vs. double bar; significant at the p <.05 level*

Total gaze duration and total fixation count for areas of interest in graphs

Total gaze duration (sum of the durations of fixations on an AOI) and total fixation count (total number of gaze fixations on an AOI) were calculated for each of four subregions (i.e., legend, pattern, x-axis, y-axis) to address how form complexity and question type variables differentially affected the processing time on individual graphic areas. Table 3 shows the mean total gaze duration and total fixation count for each region and Table 4 shows the results of repeated ANOVAs comparing total gaze duration and total fixation count in the four AOIs as a function of question type and form complexity. For the legend region, the mean total gaze duration was significantly longer for the double bar condition than for the single bar condition. For the pattern region, the mean total gaze duration was significantly longer for the double bar graphs than for the single bar graphs. Additionally, the form complexity significantly interacted with the question type, showing no difference in total gaze duration between the two question types on the single bar graphs, $t(77) = -0.38$, $p = .71$ but significantly longer total gaze

duration for the comparison question condition than for the point-locating question condition on the double bar graphs, $t(77) = -2.75$, $p = .02$.

Within the x-axis region, the mean total gaze duration was significantly longer for the comparison question condition than for the point-locating question condition. The mean total gaze duration was significantly longer for the double bar graphs than for the single bar graphs. Lastly, the question type significantly interacted with form complexity, indicating that while the mean total gaze duration was longer for the double bar graphs than for the single bar graphs in both question conditions, the mean total gaze duration difference between the single and double bar graphs was larger for the comparison question condition than for the point-locating question condition.

Within the y-axis region, the mean total gaze duration was significantly longer for the point-locating question condition than for the comparison question condition. Furthermore, the question type significantly interacted with form complexity. The follow-up comparisons showed that for the point-locating question condition, the total gaze duration was significantly longer in the single bar graphs than in the double bar graphs, $t(77) = -2.83$, $p = .007$. For the comparison question condition, there was no difference in the gaze duration between the single and double bar graphs, $t(77) = 1.14$, $p = .26$.

Table 4 also displays the results of ANOVAs comparing total fixation count in the four AOIs (legend, pattern, x-axis, y-axis) as a function of question type and form complexity. For the legend region, the mean total fixation count was significantly higher for the double bar graphs than for the single bar graphs. For the pattern region, the mean total fixation count was significantly higher for the comparison question condition than for the point-locating question condition. In addition, the mean total fixation count was significantly higher for the double bar graphs than for the single bar graphs.

Within the x-axis region, the mean total fixation count was significantly higher for the comparison question condition than for the point-locating question condition. The mean total fixation count was significantly higher for the double bar graphs than for the single bar graphs. The question type significantly interacted with form complexity, indicating that while the mean total fixation count was higher for the double bar graphs than for the single bar graphs in both question types, the mean total fixation

count difference between the single and double bar graphs was larger for the comparison question condition than for the point-locating question condition.

Within the y-axis region, the mean total fixation count was significantly higher for the point-locating question condition than for the comparison question condition. Furthermore, the question type significantly interacted with form complexity. The follow-up comparisons showed that for the point-locating question condition, the total fixation count was significantly higher in the single bar graphs than in the double bar graphs, $t(77) = -2.43$, $p = .01$. For the comparison question condition, there was no difference in the total fixation count between the single and double bar graphs, $t(77) = 0.97$, $p = .33$.

Location analysis for areas of interest in graphs

To determine participants' initial point of fixation, both with and without including the question region, the participants' first fixation point for four graphs from each of four conditions were manually coded; (1) *a single bar graph with a point-locating question*, (2) *a single bar graph with a comparison question*, (3) *a double bar graph with a point-locating question*, and (4) *a double bar graph with a comparison question*. Four graphs from each of the four conditions were selected for the location analysis that met the following criteria: graphs (a) were not the first graph of each condition presented to the participants, (b) were not the last graph of each condition presented to the participants, and (c) were correctly answered by all of the 78 participants. We excluded one participant's data from analysis because she began her inspection outside of the AOIs. All the remaining data (77 participants × 4 graphs from each condition = 308) were used for analysis. Table 5 shows the frequency of occurrence of elements participants looked at first.

Across the graph conditions, approximately 40-70% of participants looked at the question first followed by the pattern or legend areas. The three-way (question type × form complexity × AOIs) loglinear analysis produced a final model that retained the form complexity × AOIs interactions and the main effect of the AOIs. The form complexity × AOIs interaction was significant, $x^2(4) = 10.41$, $p < .05$, indicating that for the single bar graphs, more participants inspected the question region first than for the double bar graphs. The main effect of AOIs was significant, $x^2(4) = 317.19$, $p < .001$, indicating that sig-

nificantly more participants inspected the question region before the other areas.

Table 5. Locations where participants (n = 77) were looking at first.

	Pattern	Legend	X-axis	Y-axis	Question	Total
A *single* bar graph with a *point-locating* question	11 (14.3%)	12 (15.6%)	0 (0%)	0 (0%)	54 (70.1%)	77 (100%)
A *single* bar graph with a *comparison* question	12 (15.6%)	18 (23.4%)	0 (0%)	3 (3.9%)	44 (57.1%)	77 (100%)
A *double* bar graph with a *point-locating* question	18 (23.4%)	16 (20.8%)	2 (2.6%)	2 (2.6%)	39 (50.6%)	77 (100%)
A *double* bar graph with a *comparison* question	18 (23.4%)	14 (18.2%)	2 (2.6%)	2 (2.6%)	41 (53.2%)	77 (100%)

Note. Main cell entries are frequencies; entries in parentheses are the percentage of locations participants inspected first in each graph condition

Next, we excluded the question region from the AOIs to examine where the participants most frequently looked at first among the graph areas (i.e., pattern, legend, *x*-axis, *y*-axis) and conducted loglinear analysis again. The three-way (form complexity × question type × AOIs) loglinear analysis produced a final model that retained the main effect of the AOIs, $x^2(3) = 105.69$, $p < .001$, indicating that significantly more participants inspected the pattern and legend regions first than *x*- or *y*-axes. The form complexity × AOIs interaction was not significant, $x^2(3) = 6.04$, $p > .05$.

Eye transition analysis for five areas in graphs

To examine participants' scanning patterns in graphs varying task complexity and question types, their eye movements were analyzed in terms of transitions of gaze between regions (pattern, legend, *x*-axis, *y*-axis, question). We used transition matrices in which each cell shows the number of transitions from a region placed on the row to another region placed on a column. The proportion of transitions for each region was calculated by dividing the number of transitions in one region by the total numbers of transitions. Then, an Entropy *H* of transition ratio analysis, a measurement of the randomness of scanpath distribution across areas (Holmqvist et al., 2011), was calculated using the following formula: $H(R) = -\sum p(r_i) \log_2 p(r_i)$. R is the normalized transition matrix and $p(r_i)$ is the ratio (probability) of looking at a particular transition r_i. A high value of entropy indicates participants show a relatively high number of gaze transitions between regions. Entropy analysis is a fine-grained measure of the influence of specific stimuli on visual search that takes into account the context of the scanning circuit (Acartürk & Habel, 2012; Shic et al., 2008). A repeated measures ANOVA using Bonferroni's adjustment was conducted to examine the effect of question type and form complexity on the eye transitions on the graph stimuli.

Data from three students were excluded from the analysis due to partial eye movement errors. Analysis of the remaining 75 students' eye movements for the four graphs used in the location analysis resulted in a total of 2595 eye movements (511 for the single bar graph with a point-locating question, 539 for the single bar graph with a comparison question, 740 for the double bar graph with a point-locating question, and 805 for the double bar graph with a comparison question). All the movement data were manually coded and transcribed and the transition matrices were constructed for each graph (75 participants × 4 graphs = 300 matrices). The average entropy values for each graph are presented in Table 6. A 2 (question type) × 2 (form complexity) repeated ANOVA yielded a significant main effect for form complexity, $F(1, 75) = 37.28$, $p < .001$, indicating that the entropy of double bar graphs was significantly higher than the entropy of single bar graphs. This suggests that participants were making more transitions between regions in the double bar graphs than in the single bar graphs. There was also a significant main effect for question type, $F(1, 75) = 37.28$, $p < .01$, indicating that the entropy of point-locating questions was significantly higher than the entropy of comparison questions. This suggests that participants were making more transitions between regions when the point-locating questions were presented than when the comparison questions were presented. There

was no significant interaction effect between the graphic complexity and question type.

Table 6. Entropy values for the transition among AOIs.

	Mean
A *single* bar graph with a *point-locating* question	2.42 (.65)
A *single* bar graph with a *comparison* question	2.31 (.59)
A *double* bar graph with a *point-locating* question	2.84 (.36)
A *double* bar graph with a *comparison* question	2.67 (.37)

Note. Entries in parentheses are standard deviation.

In summary, our analyses showed that (1) graph processing and text processing speeds did not differ for the point-locating questions but graph processing was faster than text processing speed for the comparison questions, (2) graph processing was significantly faster than text processing in the single form condition than in the double form condition, (3) the question type mainly affected total gaze duration and fixation counts on the *x*- and *y*-axes while the form complexity affected the legend, pattern and *x*-axis regions, (4) participants tended to read questions before looking at graphs, but as the stimuli became complicated, they scanned the overall graph first by looking at the pattern or the legend, and (5) participants made more transitions between subregions for the double bar graphs than for the single bar graphs and for the point-locating question condition than for the comparison question condition.

Discussion

We used eye-tracking methods to investigate interactions between presentation modality, question types, and form complexity. In addition, eye-tracking fixation and movement data were used to determine eye gaze patterns on key locations on graphs when complexity for question type and graphic forms were manipulated.

Interactions between presentation modalities and question type

Total gaze duration, used as a proxy for processing times, varied for graph and text stimuli when complexity of question type was manipulated. The amount of time spent looking at graphs or text to answer accompanying questions did not differ when participants were given point-locating questions. However, when given comparison questions, participants took longer to process the text stimuli than the graphs. This finding is consistent with Friel et al. (2001)'s explanation that while point-locating questions simply require the extraction of a single point, comparison questions require to compare two data points and interpret relationships in the data, thereby graph viewers need longer time to answer the comparison questions.

Further, both cognitive load (Sweller, 1988; Sweller et al., 2011) and perceptual salience (Lowe, 2003) theories of learning and retaining information may account for, at least in part, the faster speed of processing for comparison questions in the graph format. Cognitive load theory (Clark et al., 2006), a frequently used framework for guiding learning and design principals, posits that information is processed in separate channels in working memory, a verbal channel for processing verbal input and a visual channel for processing visual input. Given the assumption that each channel has a limited capacity for the amount of information that can be processed at one time, researchers have argued that viewers learn more efficiently when information is presented both verbally and visually (Mayer & Moreno, 1998). Hence, it is plausible that our participants processed comparison questions more efficiently when accompanied by graphs because this condition allowed for recruiting more cross-sensory input (visual and verbal) and accompanying working memory capacity.

Additionally, the perceptual salience of the colors used to graph the data may have facilitated faster processing times in the graph condition. Even though we carefully manipulated the graph stimuli so the participants compared only the same color bars in each graph to diminish the effect of perceptual salience, previous studies have shown that color stimuli can be more effective for learning new content than black-and-white stimuli (Christ, 1975; Dwyer & Moore, 1991). Researchers have observed that colors attract viewer's attention to the relevant parts of materials (Baker & Dwyer, 2000) and that viewers prefer the colored visuals to black-and-white graphics and attend to the colored material more vigilantly (Pett & Wilson, 1996). Kleinman and Dwyer (1999) studied the effect of visual elements on information acquisition. They used simple line drawing outlines of parts of the human hears in two conditions. In one condition, parts of the heart were color-coded. In an alternative con-

dition, parts of the heart were shown in black-and-white. When asked to label the heart parts, students exposed to the condition in which parts of the heart were shown in color-coded sections yielded higher rates of accuracy than students exposed to the condition in which the heart was shown in black-and-white parts.

In the current study, the degree to which color was an important variable was dependent on the type of questions. The graph stimuli were processed faster than the text stimuli when the comparison questions were presented, but not when the point-locating questions were presented even though all graphs contained colored bars. For the comparison question, students needed to differentiate between data represented in colored bars while for the point-locating question, they needed to focus on the intersection of the x- and y-axes to answer the question. It appears that color aided the participants only when they were required to compare bars to arrive at an answer. Further studies are needed to determine the effect of color on graph and text interpretation. For example, in the text condition, two sentences (i.e., one for boy and another for girl) could be presented in two different colors and then, the effect of colors in text could be compared to those in graphs.

Related to the perceptual salience of features in graphs, the feature selection hypothesis states that visually salient features facilitate the process of filtering relevant from irrelevant information (Hegarty, Canham, & Fabrikant, 2010). For our graph stimuli in which graphic patterns (i.e., bars) are inherently salient and then readily identifiable, it was possible for students to stop searching the graph once they found the two relevant bars and thereby ignore the third bar to answer the comparison question. In contrast, for the text stimuli, students had to read the entire text and then extract the relevant information in order to answer the question. Thus, some graphs may have the benefits of quickly extracting key information over text when portions of the graph can be ignored when answering specific types of questions.

Interactions between presentation modalities and complexity of form

Given the interaction between the presentation modality and question type, it was not surprising to find an interaction between presentation modality and complexity of form. However, it was unexpected to find the inverse relationship for question types and for form types. Stu-

dents processed graphed data more quickly than text data when data were represented by single bar rather as opposed to double bars. These findings may be explained by differences in the number of variables that need to be processed for these two types of graphs. When processing single bar graphs, students must determine the relationship between the x-axis and y-axis related to a single referential category in the legend (e.g., boy). In contrast, when processing double-bar graphs, students need to differentiate between two referential categories in the legend (i.e., girl vs. boy) and then examine the relationship between the x-axis and y-axis. Our findings are consistent with Shah and Carpenter (1995)' data showing that when line graphs represent relationships between three variables (x-, y-, z- axes), college students described $x - y$ functional relationships, but seldom described x, y, z relationships even when they correctly drew all three variables on experimental graphs. The authors concluded that students made more errors and provided less complete descriptions of data on line graphs with three variables because of the necessity of keeping track of multiple relationships, making more inferences, and performing more mental transformations on the data.

Gaze duration on graph subregions varying in question type and graphic form

Overall, the students in this study spent from 61% to 70% of their total gaze duration on the axes and labeled regions and from 30% to 39% of their time viewing on the bar patterns. This is consistent with the findings reported in a study by Carpenter and Shah (1998) in which they asked college students to inspect line graphs and describe the patterns in the graphs while tracking the students' eye movements. They examined total gaze duration for five regions on the graph (pattern, x-axis, y-axis, z-axis, and title) and reported their participants spent 70-73% of their viewing time on the areas providing labels and values of the variables and 26-30% of their viewing time on the graph pattern region. That is, graph viewers spend the majority of time reading and rereading information from the axis and label regions and relatively less time on the pattern regions, which is contrary to the existing assumptions that graph comprehension is primarily or solely pattern recognition. Consistent with Carpenter and Shah (1998), data from the current study support the importance of the conceptual aspect of graph comprehension, such as interpreting labels and scales.

Question type mainly influenced the time participants spent viewing the axes. For the point-locating question, participants spent an average of 30% of the time looking at the *x*-axis. On the other hand, for the comparison question, they spent an average of 45% of the time looking at the *x*-axis. These findings suggest that the students needed extra time to encode information on the *x*-axes to answer the more complex question type which required numeral comparisons between two objects. Conversely, students spent less time viewing the *y*-axis (8%) for the comparison questions than for the point-locating questions (16%). To answer the comparison question, the students did not need to know the exact values on the *y*-axis but instead simply needed to compare the two bars in the pattern areas. Hence, the shorter total gaze duration on the *y*-axis for the more complex question may reflect the viewers' efficient search strategy for answering a specific type of questions.

Further, form complexity influenced the amount of time that participants spent looking at the legend, pattern, and *x*-axis regions. Students needed more time to view the legend and pattern when double bar graphs were presented. Unlike for the legend and pattern regions, on the *x*-axis, there was no change in appearance between the single and double bar graphs, yet, participants spent significantly more time for the *x*-axis for the double bar graphs than for the single bar graphs. Furthermore, total gaze duration and total fixation count of only the *x*-axis was influenced by all conditions, question type, form complexity, and interactions between question type and form complexity. Using a graph completion task, Peeble and Cheng (2003) analyzed subjects' average number of eye fixation transitions between graph subareas (axes, graph pattern, question, answer) and found that viewing time differences between participants were affected largely by time spent looking at the graphs' axes. Their participants tended to revisit the axes after looking at other regions of the graph. These authors suggest that frequently revisiting of the axes before and after fixating on the graphic areas helps viewers strengthen memories for the chunk of information previously viewed.

Eye location and transitions in graphs varying in question type and graphic form

The majority of participants began their searching in the question region before viewing the accompanying graph. Questions guide graph viewers' attention to certain information. Depending upon whether the question involved extracting a specific data point or comparing two data points, graph viewers identified the relevant visual features from the graph. This task-driven problem solving strategy lightens the burden on the graph viewers' working memory. Bar graphs, particularly vertically oriented bars, are more appropriate than other types of graphs when depicting quantities of physical materials because a greater quantity of items corresponds to a taller bar (Shah & Hoeffner, 2002). Thus, the point-locating questions or comparison questions used in this experiment were well matched with the bar graphs, making it more efficient for the viewers to find the key words in the question and then move to the graph to find the relevant quantitative information. Interestingly, as graphs became more complicated (i.e., single bars vs. double bars), more participants scanned the graphic pattern region (i.e., bars) before reading questions. It may be that visual search of graphical elements during the early phase of processing helps viewers build a perceptual image (Friel et al., 2001) and that initial scanning at the entry point is determined by the perceptual salient of the elements (Lim, 2004). In sum, our study showed that participants' eye movements in the graph comprehension tasks were largely task-driven and, to some degree, in the initial scanning phase, viewers were able to identify the salient features in the graph.

Further, eye transition patterns were differentially affected by both form complexity and question type. We found increasing exploration between graph subregions as graphic patterns became more complicated from single bars to double bars. Interestingly, transitions were more frequent for point-locating question condition than for comparison question condition. For the point-locating question, participants were asked to identify relationship between the *x*-axis, pattern, and *y*-axis, increasing explorations between these regions. In contrast, for the comparison question, participants mainly compared the heights of two bars in the graphic pattern region, increasing the intra-region explorations which were excluded from the entropy calculation. The analysis of transition matrix entropy, taken from fundamental information theory, has been used increasingly as a statistic measure of gaze trajectories. Shic et al., (2008) employed an entropy measure to examine the scanning patterns of toddlers with autism and Sawahata et al. (2008) assessed the relationship between a TV education program content and the entropy value of eye-gaze behaviors of TV viewers. Given that entropy values allow for comparisons of eye-

tracking patterns across stimuli and groups, applications of transition matrix entropy are expected to expand.

Conclusion

Currently, informational text makes up 50% of required reading at the elementary level and its proportion increases up to 80% in college and the work environment (National Governors Association Center for Best Practices, 2010). Informational text has info-graphic features such as graphs, tables, charts, and diagrams. Contrary to the common belief that graphs invariably help comprehension, people often have difficulty reading and interpreting information depicted in graphs (Shah, Hegarty, & Mayer, 1999). Therefore, it is important to explore the impact of using graphs to facilitate information processing and learning.

The current study aimed at investigating how college students' graph viewing strategies varied when presentation modality and graph characteristics were manipulated. Our results showed that (1) students processed graphs faster than text especially when responding to more complex questions, however, with the more complex graphs, this advantage of processing speed for graphs over text diminished; (2) students spent the majority of their time viewing information from the axes and label regions; (3) students typically read questions before viewing graphs, however, with the more complex graphs, they were more apt to initially fixate on graphical elements prior to reading the questions; and finally, (4) both graphic complexity and question types about information represented in graphs significantly affected students' eye movement patterns.

The findings of this study lead to some recommendations for educational design. Our study demonstrates that three factors, stimulus factors (i.e., graphic patterns), task characteristics (i.e., question types), and the graph viewer's goals critically affect their graph comprehension. First, good stimuli should not only convey right information but also respect limitations of human cognition and memory (Huang et al., 2006). Consideration of this nature is particularly important when information presented in graphs becomes complicated. Instead of conveying all information in one graph, it could be better to display two separate graphs having appropriate amount of information. In addition, visual cues (e.g., meaningful

colors, arrow, and pattern) can minimize search cost and working memory load (Boucheix & Lowe, 2010). For example, the relevant information in two separate graphs can be highlighted in the same color (Kosslyn, 1994) or the irrelevant information can be shaded (de Koning et al., 2010). Second, tasks types activate different schema for graph interpretation. Point-locating questions and comparison questions are well suited for bar graphs in which bars of different heights represent discrete values. On the other hand, trend judgement questions are well-suited for line graphs in which lines connect discrete values and show changes in values (Zacks & Tversky, 1999). Therefore, it is important that developers of educational materials consider whether task types conform to the types of graphic display to make graphical understanding more efficiently. Third, our study also revealed that graph viewers spend the majority of their time on comprehending conceptual information from the axes and label regions of a graph. Thus, to improve graph comprehension, students need to be informed to pay close attention to the referents and their corresponding values as labeled on the axes (Parmar & Signer, 2005). Students should learn how to adjust their searching goals, problem-solving strategies, and self-referenced feedback depending on graph conditions (i.e., graphic forms or question types).

We suggest that future studies further investigate the implications of cognitive load theory on graph comprehension. In our study, the verbal message (question) was presented in the written form. According to the cognitive load theory, spoken words would be processed through the auditory channel while pictures would be processed through the visual channel. It would be interesting to compare comprehension of graphs with spoken message to comprehension of graphs with written message. Second, to understand further the effect of graphs on information processing and learning, future research could study graph production. Most previous studies including our study have primarily focused on graph interpretation. However, as good reading does not guarantee good writing, successful graph comprehension does not guarantee successful graph construction. Graph construction could be more difficult for students to learn than graph interpretation because graph construction relies on generating new information that is not given whereas graph comprehension relies on reaction to given information (Leinhardt et al., 1990). It would be interesting to study the extent to which stimulus complexity, task types, and learners'

characteristics affect graph construction. . Finally, for the location analysis and eye transition analysis, we selected four graphs from each condition and analyzed 78 participants' first fixation point and eye movements between regions. Future studies should replicate our findings with a larger sample.

Acknowledgements

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Appendix 1. Experiment stimulus samples. Order of words (i.e., 'boy and girl' in legend and 'dogs, turtles, and birds' in the x-axis) and colors in legend and bars are randomized. Words were presented in black Arial 15 (in axes and legend) and 20 (questions) point fonts. In the experiment, questions were presented the right side of the graph/text.

Single bar graph with a *point-locating* question
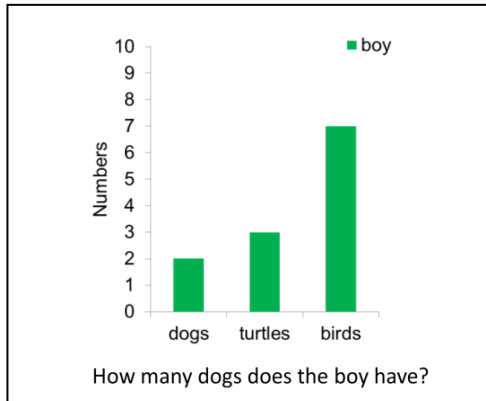
Single bar graph with a *comparison* question

The girl has seven turtle, six dogs, and four birds.

How many birds does the girl have?
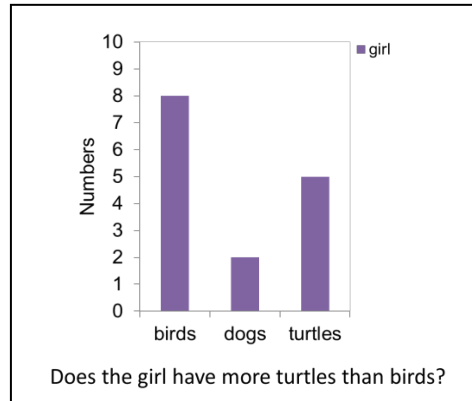
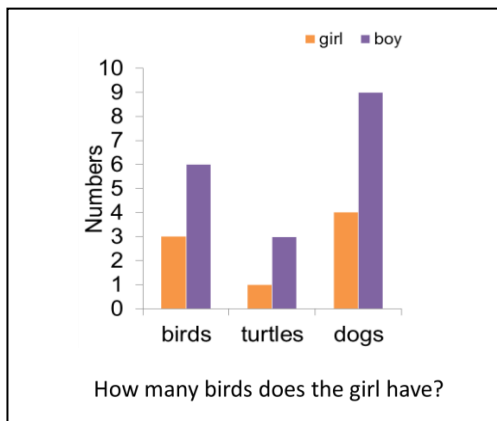*Single sentence* text with a *point-locating* question

The boy has three birds, five turtles, and one dog.

Does the boy have more dogs than turtles?

Single sentence question with a *comparison* question

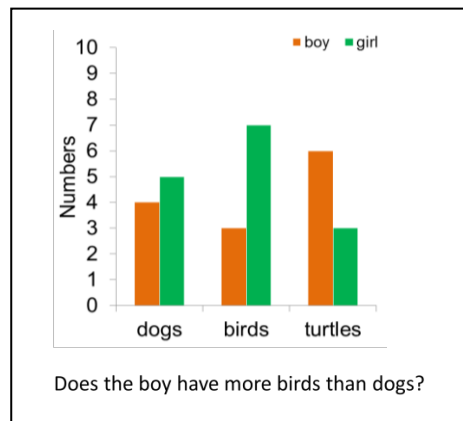

Double bar graph with a *point-locating* question

Double bar graph with a *comparison* question

The girl has six dogs, two birds, and three turtles.

The boy has two dogs, one bird, and five turtles.

How many turtles does the boy have?

Double sentence text with a *point-locating* question

The boy has three birds , five dogs , and one turtle.

The girl has six birds, three dogs, and seven turtles.

Does the girl have more birds than turtles?

Double sentence text with a *comparison* question