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Authors
Tsai, Evelyn Hsin-I
Hahn, Yoojin
Siegler, Robert

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What Do Children Encode from Graphs?

Evelyn Hsin-I Tsai (et2734@tc.columbia.edu)[1], Yoojin Hahn[1] & Robert S. Siegler[1]
[1]Department of Human Development, Teachers College, Columbia University

Abstract

The ability to interpret graphs is crucial for educational and professional success, yet many people struggle with graph comprehension. This study investigates how children process graphical information and what graph elements they attend to, encode, and retain. Middle school children completed three tasks. In the Description Task, participants described a graph either while viewing it or from memory. The Recognition Task assessed participants' ability to detect and remember differences in specific components (i.e., axes, scales, and trends) between two graphs. The Slope Judgment Task examined whether judgments of rate of change relied more on pictorial cues (e.g., visual steepness) or semantic cues (e.g., scale values). We found that children consistently extracted and recalled pictorial features across tasks, whereas quantitative semantic features such as axis scales were encoded and retained less accurately. These findings clarify the nature of children's graph encoding and have implications for graph comprehension instruction.

Keywords: graph comprehension; graph encoding; data visualization; math learning

Introduction

Graphs are widely used in scientific communication, news articles, and social media to convey data (Divecha et al., 2023; Kirsten et al., 2025; Zhao & Cummins, 2024). Adults rely on graphs when making decisions about health, finance, public policy, and daily life (Holder & Bearfield, 2023; Kothakota & Kiss, 2020; van Weert, 2021). Children encounter graphs throughout science, mathematics, and social studies curricula from elementary through high school (Zucker et al., 2015). Reflecting this central role of graphs, the Common Core State Standards (CCSS), the Program for International Student Assessment (PISA), and the Next Generation Science Standards all emphasize graph literacy (National Governors Association Center for Best Practices, 2010; National Research Council, 2013; PISA Mathematics Framework, 2022). Accurately interpreting graphs is essential for academic success and effective decision-making in occupational and everyday contexts (Mandinach, 2012; Soler Wenglein et al., 2025; World Economic Forum, 2011).

Despite this emphasis, many children and adults struggle to compute slopes, extrapolate values, and analyze data depicted in graphs (Binali et al., 2022; Reimers & Harvey, 2024). On the TIMSS (2013) assessment, only 29% of U.S. eighth graders correctly calculated the mean of data points in a line graph. These difficulties persist into high school and college, where students commonly confuse slope with height of values on the y-axis (Cho & Nagle, 2017; Planinic et al., 2012). Even adults frequently misread exponential trends (Lammers et al., 2020) and have trouble recalling quantitative information they have just viewed in graphs (Fischer et al., 2023; van Weert et al., 2021). Such widespread difficulties are concerning, given the increasing need to understand graphs in modern life (Börner et al., 2019; Fansher et al., 2022).

Although graph comprehension is a major instructional objective in middle school, relatively little is known about the cognitive processes underlying children's graph understanding or how these processes compare with those of adults. Most prior research has tested adults' performance on specific graph-reading tasks (e.g., reading of data points), while few studies have examined the information children spontaneously extract from graphs, such as what they perceive as most important or how they would describe a graph to others. These spontaneous processes more closely reflect everyday interactions with graphs.

Understanding which information is prioritized, neglected, or misrepresented in recall of graphs is essential for explaining why certain graph comprehension errors occur. In the following sections, we first review cognitive processes involved in graph encoding and comprehension and then introduce the present study examining what children encode and recall from graphs.

Semantic and Pictorial Variables in Graph Comprehension

Comprehending graphs requires iterative cycles of perceiving, interpreting, and integrating information from multiple regions of a graph (Carpenter & Shah, 1998). These include pictorial variables—such as trend direction, relation strength, shape (linear or nonlinear), format (bar, line, pie, scatterplot), and number of data points—and semantic variables, which specify what the depicted data represent. Semantic information can be quantitative (scales, units of measurement, numerical values) or qualitative (titles, captions, labels). Pictorial information is generally displayed in the rectangle formed by the x-and y-axes; semantic information is generally displayed outside the axes, though graph titles and labels of variables are sometimes presented within the rectangle. Semantic features are typically expressed in words and numbers; Pictorial features are typically expressed with symbols other than words or numbers, such as lines, bars, and dots. Prior research has often examined how individuals interpret pictorial features of graphs (e.g., trends, slope), but relatively little is known about what semantic information, such as axis labels and scales, people spontaneously encode when viewing graphs.

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The necessity of processing both pictorial and semantic features is illustrated in Figure 1. The graph in the top-left panel shows a pattern in which the y-axis values are initially high and then decline as the x-axis values increase. However, without quantitative semantic information such as axis scales, the graph is uninterpretable; the same pictorial pattern could reflect a rapid change or a trivial one, depending on how the axes are scaled. Likewise, without qualitative semantic information such as axis labels, there is no way to know what the pattern represents. Two graphs that look identical could convey entirely different meanings—for example, if the y-axis were labeled "Snowfall (in inches)" rather than "Rainfall (in mm)." Only in the bottom-right panel, where both labels and scales are present, can the graph be interpreted both qualitatively and quantitatively. That panel indicates that rainfall was high at the beginning of the month and gradually decreased.

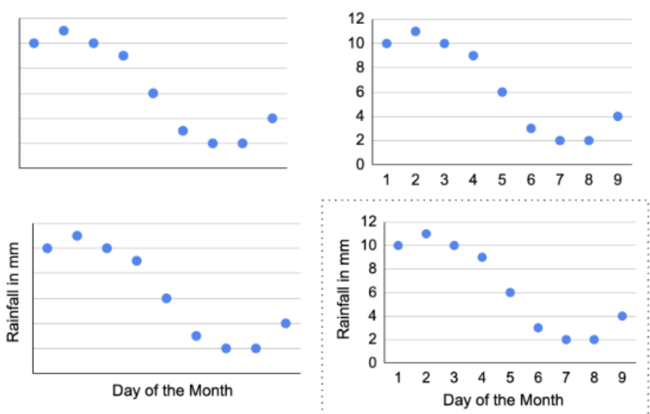

Figure 1: Effect of semantic and pictorial variables on interpretability of graphs.

Attending to variable labels and numerical values on the x- and y-axes is crucial to graph comprehension. Eye-tracking studies indicate that skilled graph readers frequently examine semantic features (e.g., axis scales and labels) and show integrative eye-movement patterns among axes, legends, and data (i.e., shifting between semantic and pictorial information) (Atkins & McNeal, 2018; Harsh et al., 2020; Ruf et al., 2023). Novices, in contrast, rely more on titles and external cues (such as question prompts or answer choices), fixate on seductive details, and are less accurate on graph comprehension tasks (Atkins & McNeal, 2018; Harsh et al., 2020).

Padilla et al. (2018) proposed a dual-process account of visualization comprehension, in which fast, automatic perceptual processes often guide initial interpretations, whereas analytical processes, such as those required for processing semantic information, are typically slower and more effortful. Consistent with this model, Hahn and Siegler (under review) found that adults relied more on pictorial than semantic variables when extrapolating from graphs. This bias produced more accurate extrapolations when the x-axis represented continuous variables (consistent with trend-based extrapolation) but poorer performance when the x-axis represented categorical variables (which require attention to axis scale rather than the trend in the display).

Graph description tasks provide a way of obtaining direct evidence of what people spontaneously encode when viewing graphs. For example, Xi (2010) found that adults organize their description of graphs around trends, or visual "chunks" corresponding to changes in direction or slope. However, little is known about children's encoding of graphs. This is unfortunate; childhood is the period during which graph literacy is taught in school and develops most rapidly, making it a crucial window for understanding how graphing skills emerge.

A few recent studies of graph comprehension with elementary school children show that they can extract basic pictorial information and distinguish visual features of graphs, such as the location and value of data points, and can judge whether a scatterplot is ascending or descending (Ciccione et al., 2023; Panavas et al., 2022). However, these perceptual judgment tasks did not require integrating pictorial with semantic features to interpret relations in the graph, leaving unclear whether and how children engage in the deeper processing required for understanding graphs. A key goal of the present study is therefore to examine what information middle school children spontaneously encode from graphs, whether they integrate semantic and pictorial features, and how encoding varies with task demands.

The Present Study

The present study examined how sixth and seventh grade students encode, retain, and apply pictorial and semantic information when interpreting graphs. These grade levels were selected because graph comprehension instruction typically begins in fifth grade and is emphasized throughout middle school (National Governors Association Center for Best Practices, 2010), so by sixth grade, all children likely would have received at least one year of relevant instruction in graph comprehension, making this a critical period for acquisition of these concepts.

Prior research suggests that adults rely heavily on perceptual cues, such as slopes and visual patterns, while often overlooking semantic information presented in x- and y-axis labels (Hahn & Siegler, under review). If this bias reflects a fundamental limitation of graph processing, it should be evident by middle school age. Accordingly, the present study investigates whether middle school children overweight pictorial features (e.g., trends) and underweight semantic features (e.g., labels and scales) when interpreting graphs, and whether this tendency varies across task demands.

To address these questions, we designed three tasks: a graph recognition task, a slope judgment task, and a graph description task. These tasks allow us to examine how different contexts may elicit distinct processing strategies. We compared: (1) accuracy of encoding and memory for pictorial and semantic features (2) the extent to which each type of feature influences slope judgments, (3) the richness and structure of children's spontaneous graph descriptions. Our hypotheses were:

Hypothesis 1: In the Recognition Task, pictorial features (e.g., trends) would be encoded more accurately than semantic features (e.g., labels).

Hypothesis 2: In the Slope Judgment Task, pictorial features (i.e., the visual trend) would guide slope judgments more than semantic features (i.e., the y-axis scale), reflecting insufficient attention to axes.

Hypothesis 3: In the Description Task, which requires deeper meaning extraction (i.e., identifying the most important information in a graph), participants will encode qualitative semantic information (e.g., labels of variables) more accurately than quantitative semantic information (e.g., scale values), because the former is more central to articulating the graph's meaning. Pictorial features are expected to be described accurately as well.

Methods

Participants

We recruited 38 U.S. middle school children (16 sixth graders and 22 seventh graders; M_{age} = 12.18, SD_{age} = 0.69; 21 female) from a private school in New Jersey. All children provided audio responses to each question and passed the attention checks. The school's demographic composition was 78% White, 14% Asian, 3% Black, 2% Hispanic, and 3% Biracial. Students were quite high achieving, scoring, on average, at the 95th percentile on the state standardized math achievement test (New Jersey Department of Education, 2023).

Stimuli and Task

We employed a within-subjects factorial design in which participants completed a Recognition Task and a Description Task, administered under two conditions — Viewing (responding while the graph remained visible) and Memory (responding after the graph disappeared.) This yielded four conditions: Description–Viewing, Description–Memory, Recognition–Viewing, and Recognition–Memory. Participants also completed a Slope Judgment Task, in which they compared rates of change between two graphs. The four conditions of the Description and Recognition tasks were presented in randomized, counterbalanced order, followed by the Slope Judgment Task.

Recognition Task The Recognition Task consisted of 20 trials (10 per condition). To differentiate failures of encoding from failures of retrieval, participants completed the task under both Viewing and Memory conditions. In the Viewing condition, participants viewed a graph for 15 seconds, after which a second graph was presented next to the first graph. Participants had unlimited time to indicate whether the two graphs represented the same or different information. In the Memory condition, the first graph disappeared after 15 seconds, the second graph immediately appeared, and participants made the same binary judgment. When participants responded "different," they were asked to describe how the graphs differed.

Across trials, the specific dimension that was similar or different between the two graphs was manipulated. On some trials, the dimension that differed was semantic (e.g., axis label or scale); on other trials, the differing dimension was pictorial (e.g., slope steepness). There were three Same Trials (the two graphs were identical), three Semantically Different Trials (graphs differed on a semantic dimension), and two Pictorially Different Trials (graphs differed on a pictorial dimension). Trials were presented in a randomized order. Figure 2 illustrates how two pictorially identical graphs can convey very different meanings about the relation between unemployment rates and years of education.

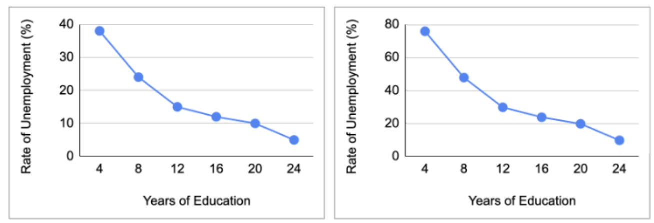

Figure 2: Example of a semantically different trial.

All trials included line graphs with six data points and monotonic, non-linear trends with evenly spaced whole numbers along the y-axis. Both x and y axes depicted ratio variables. Axis labels and scales were written in black, and data points were plotted in blue.

Slope Judgement Task The Slope Judgment Task had four trials. Participants viewed pairs of increasing graphs presented side-by-side, one truncated the other not, and judged which graph showed a more rapid increase in the dependent variable. Stimuli varied by (1) presence of a truncation indicator ("Z" symbol present or absent on the Y axis), and (2) pictorial–numerical consistency. On Consistent trials, the truncated graph both appeared steeper and had a larger numerical slope than the non-truncated graph. On Inconsistent trials, the truncated graph appeared steeper (due to a smaller range of values on the Y-axis) but had a smaller numerical slope than the non-truncated graph. Trial order was randomized, and participants had unlimited time to respond. Accuracy was scored as correct or incorrect.

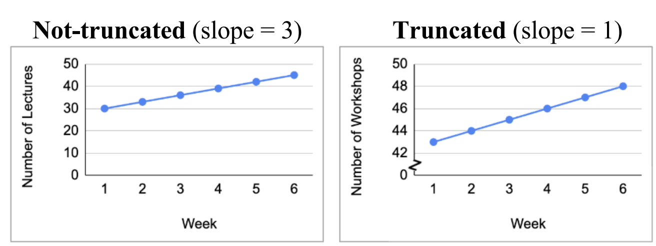

Figure 2: Example of pictorial slope ≠ numerical slope.

Description Task The Description Task consisted of 8 trials, 4 per condition. Participants were asked to orally describe the graph as if they were explaining it to a friend who did not see it, starting with the most important information, and being as detailed as possible. In the Viewing condition, participants viewed a graph for 20 seconds and then described the graph while it remained visible on the screen. In the Memory condition, participants were told that the graph would disappear after 20 seconds and that they would need to describe the graph from memory. Stimuli varied by (1) slope direction (increasing vs. decreasing), and (2) number of data points (4 vs. 8). Responses were recorded via microphone, and no changes of answers were permitted.

In coding performance on the Description Task, pictorial features were scored 1 if the participant stated the trend direction. Qualitative semantic features were scored 1 if both x- and y-axis labels were mentioned, 0.5 if one label was mentioned, and 0 if neither label was mentioned. Quantitative semantic features were scored 1 if both x- and y-axis numerical scales were mentioned, 0.5 if only one scale was mentioned, and 0 if neither scale was mentioned.

Procedure

All study procedures were approved by the Institutional Review Board at Teachers College, Columbia University. The experiment was programmed and administered online using Gorilla Experiment Builder. The participants' mathematics teacher distributed the study link through the school's learning management system for students to complete at home. Participants used a computer with a functioning microphone and the Chrome browser. Parental consent and child assent were obtained for all participating students. The session lasted approximately 30 minutes.

Results

Graph Recognition Task

Accuracy (proportion correct) was analyzed as the dependent variable using generalized linear mixed models (GLMMs) with binomial logistic regression and random intercepts for participants. Fixed effects included task condition and the dimension that varied.

Effect on Graph Recognition of Task (Viewing vs. Memory) The middle school children's accuracy did not differ between the Viewing (70%) and Memory conditions (68%), $b = 0.10$, $SE = 0.18$, $z = 0.55$, $p = .581$. In other words, given that accuracy was no higher when both graphs remained visible than when judgments relied on memory, the limitation appears to reflect failures to encode graph features rather than failures to retrieve encoded information.

Effect on Graph Recognition of Dimension that Varied In both conditions, middle school children were more accurate at detecting differences in pictorial variables (Memory condition: 85% correct, Viewing condition: 87% correct) than differences in semantic variables (Memory condition: 36% correct, Viewing condition: 28% correct), $b = 2.57$, $SE = 0.46$, $z = 5.57$, $p < .001$. Consistent with our hypothesis, pictorial features were encoded and retrieved far more accurately than semantic features when both graphs were present and when one graph had to be remembered. When pictorial features of the two graphs were the same, children usually judged the graphs as identical, even when the axis labels or scales differed in ways that showed that the meaning of the graphs differed. When the children noted that a dimension differed, they correctly specified the dimension that differed on more than 90% of trials for both pictorial and semantic differences.

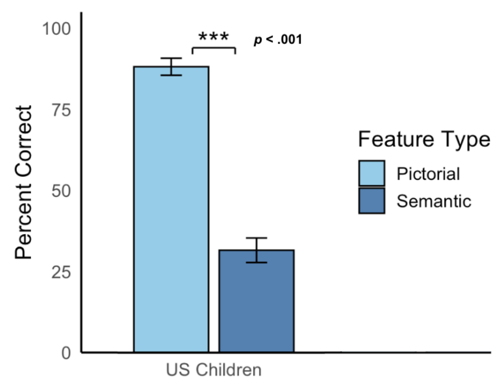

Figure 3: Middle school children's accuracy on the graph recognition task by the dimension that varied

Slope Judgement Task

We conducted a binomial logistic generalized linear mixed model with pictorial–numerical consistency and presence of truncation indicator as predictors.

Consistent with our hypothesis, the children were much more accurate on Consistent trials (96%), that is trial where the same graph showed a greater slope both pictorially and numerically, than on Inconsistent trials (7%), where one graph had a greater pictorial slope but the other had a greater numerical slope, $b = 16.48$, $SE = 3.612$, $z = 4.5$, $p < .001$. Thus, children's slope judgments were almost entirely guided by pictorial cues (visual steepness), with almost no attention to numerical values on the y-axis. Accuracy did not differ between whether the Y-axis of the truncated graph included a "Z" to indicate a discontinuity (51%) or no such indicator (52%), $b = 0.00$, $SE = 1.24$, $z = 0.00$, $p = 1.000$, indicating that the symbol did not affect children's recognition of truncation.

Graph Description Task

A generalized multivariate mixed-effects model was used with random intercepts for participants.

Description while Viewing While the graph remained visible, children described all three types of features of the graph with similarly high accuracy (pictorial features: 82% correct; qualitative semantic features: 80% correct; quantitative semantic features: 78% correct). Pairwise contrasts showed no significant differences in accuracy on the three feature types (all $|t| < 0.76$, all $p > .05$).

Description from Memory When children described graphs from memory, accuracy differed across feature types. Pictorial features were described more accurately than qualitative semantic features (80% vs. 69%, $t = 2.73$, $p = .019$), and both were described more accurately than quantitative semantic features (46%) (Pic–Quant: $t = 8.03$, $p < .001$; Qual–Quant: $t = 5.30$, $p < .001$).

Table 1: Accuracy by feature type across viewing and memory conditions in the graph description task

Feature Type	Description while Viewing		Description from Memory	
	M	*SD*	*M*	*SD*
Pictorial	83	39	80	40
Qualitative Semantic	80	34	69	39
Quantitative Semantic	78	36	46	40

Descriptions of pictorial variables were equally accurate regardless of whether the graphs were present or absent. Recall of qualitative semantic information was slightly lower in the Memory condition than in the Viewing condition ($t = -2.84$, $p = .019$). Much larger differences were observed for recall of quantitative semantic features ($t = -7.85$, $p < .001$). In other words, pictorial information was recalled well when the task involved explicit verbal comparisons of graphs, regardless of whether the graphs were present or needed to be recalled, but quantitative semantic information was poorly recalled from memory and was often not mentioned.

Children produced longer descriptions in the viewing condition ($M = 78$ words) than in the memory condition ($M = 53$ words, $b = 24.63$, $SE = 2.64$, $t = 9.34$, $p < .001$), indicating that visual access to the graph supported more detailed responses.

Discussion

Bias Toward Pictorial Over Semantic Features

We examined the types of information U.S. middle school students spontaneously encode and retain when interpreting graphs. As hypothesized, pictorial features were encoded and retrieved far more accurately than semantic features in the Recognition Task. Consistent with prior research (e.g., Hahn & Siegler), the difference indicates that graph encoding is biased toward pictorial trends, whereas semantic information, especially semantic quantitative information, about underlying data relations is often overlooked. This result is consistent with Fuzzy Trace Theory (Reyna & Brainerd, 1995; Reyna & Brainerd, 2011), which emphasizes reliance on gist over verbatim information. In the context of graph comprehension, gist representations, such as those of overall trend direction and graph shape, were processed more accurately than verbatim information, such as numerical scale values and units.

Similarly, in the Slope Judgment Task, children's interpretations of rates of change were guided primarily by pictorial cues (i.e., visual steepness) rather than semantic cues (i.e., y-axis numerical scale values). The truncation symbol did not improve performance, suggesting that children paid little attention to indicators that the y-axis did not begin at zero. These findings indicate a strong bias toward visual trends but limited use and incorporation of semantic information that is also necessary for accurate interpretation.

Semantic Information in Graph Descriptions

In the Description Task, we expected semantic information to feature prominently in participants' verbal descriptions, given that describing a graph typically requires attention to the graph's content (Tsuji & Lindgaard, 2014; Xi, 2010). This prediction was partially supported. Children reported pictorial information (trend direction) and qualitative semantic information (x- and y-axis labels) quite accurately, likely because both convey the graph's gist. Pictorial features indicate the shape of the relation between variables, whereas labels define the variables and what the graph represents. In contrast, quantitative semantic information (e.g., numerical values on x- and y-axis scales) were reported less accurately and less frequently.

One explanation for this pattern is that pictorial features are more perceptually salient and therefore easier to encode and describe across tasks. Another possibility may be differences in cognitive load and working-memory demands, making quantitative information less likely to be encoded and retained. Encoding and interpreting semantic graph features, especially quantitative features such as scale values and units, requires maintaining multiple symbolic elements in working memory and integrating them with pictorial patterns, which produces a high intrinsic cognitive load. The difficulty of maintaining all of this information is likely greater for children whose working-memory capacity is still developing, than for adults (Ouwehand et al., 2025).

The Role of Task Demands in Graph Processing

These findings also highlight the role of task demands. Tasks that require explicit description of a graph's content appear to promote attention to qualitative semantic information, whereas tasks that seem visually solvable from looking at trend steepness can lead to overreliance on pictorial features. Thus, successful graph comprehension depends not only on encoding visual and semantic information but also on integrating these sources of information.

Together, these results suggest that the tasks of encoding and verbally describing graph content depend on partially distinct cognitive processes. When asked to do so, children accurately described qualitative semantic features, but the same children usually did not use those features when judging whether two graphs were equivalent. These findings underscore that differences among task demands can shape what information is encoded, processed, and applied to reaching conclusions on graph comprehension problems.

Educational Implications

The present findings have implications for instruction in graph literacy. Graph instruction often emphasizes visual decoding (e.g., finding points with specific coordinates, noting whether a line increases or decreases, comparing bar heights). However, accurate interpretation of graphs requires encoding both qualitative semantic information (e.g., variable names) and quantitative semantic information (e.g., scale values and units). Instruction should explicitly teach students how to locate relevant semantic information and how to integrate semantic and pictorial cues.

One useful instructional task might be to present problems with conflicts between pictorial and semantic cues—for example, pairing a steep upward line with axis scales that contradict the visual impression, as in the Recognition Task of the present study. Presenting such examples, along with clear teacher explanations of why considering the image by itself can be misleading, may help students understand that graphs with identical pictorial patterns can convey different meanings depending on their semantic features. More generally, graph literacy instruction should help students integrate pictorial and semantic information.

Future Directions

The sample size of children included in the present study was relatively small; larger samples should be used to replicate the findings. To determine whether these findings hold with older individuals, parallel studies should be conducted with high school students and adults; this would produce a more comprehensive understanding of developmental trajectories of graph comprehension.

Examining integration of semantic and pictorial variables with other graph formats (such as bar graphs and scatterplots and graphs with different slope direction and magnitudes would also be useful for testing the generality of the findings. Moreover, eye-tracking studies could provide more direct measures of attention to y-axis variables and scale values and could indicate how children order attention to pictorial information, semantic qualitative information, and semantic quantitative information during graph processing. These are all important goals for future research.

Conclusion

Across graph recognition, slope judgment, and graph description tasks, middle school students consistently encoded and recalled pictorial information more accurately than quantitative semantic information (e.g., axis scales and numerical values). Middle school children also relied almost entirely on visual steepness when determining rates of change, even when semantic cues indicated a different interpretation was appropriate. These findings suggest that effective instruction should help students learn to attend to and integrate axis scale values, axis labels, and visual patterns to support accurate graph comprehension.

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