Picturing student progress : teachers' comprehension of curriculum-based measurement progress graphs

Bosch, R.M. van den

Author: Bosch, R.M. van den
Title: Picturing student progress : teachers' comprehension of curriculum-based measurement progress graphs
Issue Date: 2018-11-22

TEACHERS' INSPECTION PATTERNS OF CURRICULUM-BASED MEASUREMENT PROGRESS GRAPHS: AN EYE-TRACKING STUDY

Submitted as:
van den Bosch, R. M., Espin, C. A., Sikkema-de Jong, M. T., Chung, S., Boender, P., & Saab, N. Teachers' inspection patterns of curriculum-based measurement progress-monitoring graphs: An eye-tracking study.

CHAPTER 4

ABSTRACT

In this explorative, descriptive eye-tracking study we examined how teachers visually inspect curriculum-based measurement (CBM) progress graphs. More specifically, we examined how long teachers looked at the various elements of CBM graphs, and whether they inspected those elements in a logical sequence. Participants were 17 fifth- and sixth-grade teachers who had collected CBM progress-monitoring data for students with reading difficulties/dyslexia in their classes over a period of 10-12 weeks. Data from a CBM expert were collected to provide a frame of reference for interpreting the teachers' eye-tracking data. Participants described two CBM graphs while their eye-movements were registered. Results revealed that, as a group, teachers devoted less visual attention to important graph elements and inspected the graph elements in a less logical sequence than did the CBM expert; however, there was variability in teachers' patterns of graph inspection. Directions for future studies and implications for practice are discussed.

TEACHERS' INSPECTION PATTERNS OF CURRICULUM-BASED MEASUREMENT PROGRESS GRAPHS: AN EYE-TRACKING STUDY

Teachers who work with students with severe and persistent reading difficulties are expected to provide the students with additional, specialized, individualized reading instruction, and to closely monitor the progress of the students and to evaluate the effectiveness of instruction. One system particularly suited for closely monitoring student progress is curriculum-based measurement (CBM; Deno, 1985).

Curriculum-based Measurement (CBM)

CBM is a system designed for teachers to use to monitor the progress of students with learning difficulties, and to evaluate the effectiveness of instruction for those students (Deno, 1985, 2003). CBM involves frequent, repeated, administration of short, simple measures that sample global performance in an academic area, for example, in reading. Scores from the measures are placed on a progress graph that depicts an individual student's progress over time.

CBM progress graphs typically include baseline data for the student and his/her peers, a long-range goal, a goal line that extends from the baseline to the long-range goal, and several instructional phases that are separated by vertical lines. Within each phase of instruction, data points representing the student's scores on the CBM measures and a slope line representing the student's rate of growth within that phase are depicted.

The progress graph lies at the heart of CBM. The graph depicts student growth in response to the instructional program being provided, and thus, forms the basis for instructional decision-making (Deno, 1985). Teachers are supposed to visually inspect the CBM graphs on a regular and frequent basis to evaluate whether students are making adequate progress and are benefitting from instruction. If the student's slope line is below and/or less steep than the goal line, it signals a need for change in instruction. If the slope line is above and steeper than the goal line, it signals a need to raise the long-range goal. CBM graphs not only guide teachers' instructional decision-making, they also foster communication in team meetings or parent conferences about student progress and about the effects of instructional programs (Deno, 2013).

In order to use the CBM graphs to make instructional decisions, and to communicate information about student progress and the effects of instructional programs, teachers must be able to read and interpret – that is, to comprehend – the CBM graphs. However, it is only recently that research has addressed teachers' ability to comprehend CBM graphs.

CBM Graph Comprehension

Graph comprehension is defined as the ability to "derive meaning from graphs" (Friel, Curcio, & Bright, 2001, p. 132) and refers to a graph viewer's ability to read and interpret graphs. Graph comprehension is influenced by both the characteristics of the graph and of the viewer (Friel et al., 2001), each of which has been addressed in recent research on CBM graph comprehension. With regard to the characteristics of the graph, research has demonstrated that factors such as the relative position of the slope line to the goal line and the relative position of slope lines across adjacent instructional phases, affect the ease with which viewers answer instructional decision-making questions (Espin, Saab, Pat-El, Boender, & van der Veen, 2018). In addition, research has demonstrated that the magnitude of the slope, the variability in the data, the presence of outliers in the data, and the use of visual aids all affect CBM graph comprehension (e.g., Newell & Christ, 2017; van Norman & Christ, 2016).

With regard to the characteristics of the viewer, a series of descriptive studies have demonstrated that both preservice and inservice teachers have difficulty comprehending CBM graphs (Espin, Wayman, Deno, McMaster, & de Rooij, 2017; Wagner, Hammerschmidt-Snidarich, Espin, Seifert, & McMaster, 2017). Because the focus of the present study is on the CBM graph viewer, we review those studies in more detail in the following section.

CBM Graph Comprehension: The Viewer

In one of the first studies conducted to examine teachers' CBM graph comprehension, Espin et al. (2017) asked 14 inservice teachers to "think out loud" while reading and describing CBM graphs. Teachers' thinks-alouds were rated as to the extent to which they reflected knowledge about CBM, and were scored for accuracy, coherence, specificity, and reflectivity. Scores for the higher- and lower-rated think-alouds were then compared. Higher-rated think-alouds were found to be more accurate, coherent, specific, and reflective than lower-rated think-alouds. Interestingly, no relation was found between the CBM knowledge ratings of teachers' think-alouds and teachers' years of experience with using CBM.

In a subsequent study, Wagner et al. (2017) used the think-aloud approach to examine CBM graph comprehension for preservice teachers (N = 36). To provide a frame of reference for interpreting the preservice teachers' data, a small group of "gold-standard" CBM experts (N = 3) also was included in the study. These gold-standard experts were pioneers of CBM. Both preservice teachers and CBM experts completed think-alouds for two researcher-made CBM graphs. Results revealed that the preservice teachers were less accurate, complete, coherent, specific, and reflective in their think-alouds than the CBM experts.

Although the results of the Wagner et al. (2017) and Espin et al. (2017) studies demonstrated that CBM graph comprehension was difficult for teachers, the Wagner et al. study included only preservice teachers, and the Espin et al. study included only a small number of inservice teachers. In addition, in neither study the question was addressed of whether difficulties with CBM graph comprehension were unique to teachers. In other words, were teachers not good at reading and interpreting CBM graphs, or were the CBM graphs difficult to read and interpret?

In a subsequent study, van den Bosch, Espin, Chung, and Saab (2017) replicated and extended Wagner et al.'s (2017) study. Participants were inservice teachers (*N* = 23) and three small groups of "gold-standard" experts: General-graph experts who had PhDs and were assistant professors in statistics (*N* = 2), Education-graph experts who had PhDs and worked for a Dutch educational assessment company (*N* = 2), and CBM experts (*N* = 3). For the CBM experts, the data from the Wagner et al. study were used (with permission). All participants completed think-alouds for the same researcher-made CBM graphs that had been used by Wagner et al. While completing the think-alouds, participants' eye movements were registered. Teachers additionally completed think-alouds for two graphs from students with reading difficulties/dyslexia. The teachers had collected CBM progress-monitoring data for these students over a period of 10 to 12 weeks. The results of this study related to the think-aloud data were reported in van den Bosch et al., and revealed that, similar to the findings of Wagner et al. for preservice teachers, inservice teachers had more difficulty reading and interpreting the researcher-made CBM graphs than did the CBM experts. However, the data also revealed that difficulties with CBM graph comprehension were not unique to teachers and, further, that teachers experienced difficulties with the interpretation of both researcher-made and student graphs.

In the present paper, we report the results of this study related to the eye-movement data. However, because the think-aloud and eye-movement data from the study are closely linked, in the following section we provide a more detailed description of the methods and results related to the think-aloud data. This information is important for understanding the design and the methods of the present study.

CBM Graph Comprehension: Teachers versus "Gold-Standard" Experts

The think-aloud data that were collected as part of the larger study were coded for accuracy, completeness, sequential coherence, data-to-data comparisons, data-to-goal comparisons, and data-to-instruction links (see van den Bosch et al., 2017). *Accuracy* reflected the percentage of statements made in the think-alouds that were correct. *Completeness* reflected the number of relevant graph elements mentioned in the think-alouds (out of 9). *Sequential coherence* reflected the percentage of statements made in the think-alouds that followed an "ideal" sequence. The ideal sequence represented the order in which CBM graphs are used for instructional decision-making, and included *Framing* (i.e., describing the set-up of the graph), *Baseline*, *Goal setting*, *Instructional phases 0 to 4*, and *Goal achievement* (Espin et al., 2017). *Data-to-data comparisons* and *data-to-goal comparisons* – collectively referred to as *within-the-data comparisons* – reflected the number of times participants compared the data points or slope lines from one instructional phase to another or the number of times they compared the data points or slope lines to the long-range goal or goal line. Finally, *data-to-instruction links* reflected the number of times participants linked the data points or slope lines to the student's reading instruction.

For the researcher-made graphs, the teachers' think-alouds were, on average, found to be less complete and coherent than those of the CBM experts (van den Bosch et al., 2017). Moreover, the data revealed that teachers made, on average, fewer within-the-data comparisons (i.e., data-to-data and data-to-goal comparisons) and fewer data-to-instruction links than the CBM experts.

CBM graph-comprehension difficulties, however, were not unique to teachers. The General-graph and Education-graph experts also were less complete and coherent in their think-alouds than the CBM experts, and also made fewer within-the-data comparisons and fewer data-to-instruction links than the CBM experts (van den Bosch et al., 2017).

With regard to the student graphs, the researchers had anticipated that teachers would be more likely to make data-to-instruction links for these graphs than for the researcher-made graphs because the data would be more "real" for the teachers, and thus more closely linked to the students' instruction. However, results did not support this assumption. Whereas for the researcher-made graphs 11 out of 23 teachers made at least one data-to-instruction link, for the student graphs only 6 out of 23 teachers made at least one such link (van den Bosch et al., 2017).

In sum, and as mentioned earlier, the results of the think-aloud portion of the study demonstrated that: (1) CBM graph comprehension was not simple; (2) difficulties with CBM graph comprehension were not unique to teachers; and (3) difficulties with CBM graph comprehension were not limited to researcher-made graphs. What could not be discerned from the think-aloud data was whether teachers' difficulties with CBM graph comprehension would be reflected in the ways in which they inspected the graphs. By collecting eye-movement data, we could examine teachers' patterns of CBM graph inspection as they read and interpreted the graphs. To register the teachers' eye-movements, we used eye-tracking technology.

Eye Tracking

Eye-tracking technology is used to register people's eye movements while completing a visual task. Eye movements reveal how people allocate their visual attention while viewing the stimulus and completing the task, and can provide insight into the cognitive strategies that people use while completing the task (Duchowski, 2017). In various fields of research, such as medicine, sports, biology, and meteorology, eye-tracking technology has been used to examine differences between experts and novices in the comprehension of visual stimuli and in the strategies used to complete visual tasks (e.g., Al-Moteri, Symmons, Plummer, & Cooper, 2017; Canham & Hegarty, 2010; Gegenfurthner, Lehtinen, & Säljö, 2011; Jarodzka, Scheiter, Gerjets, & van Gog, 2010). A consistent key finding that has emerged from these "expert/novice" studies is that, compared to novices, experts devote more attention to the task-relevant parts of the visual stimuli and approach visual tasks in a more goal-directed or systematic manner.

Specific to the field of graph comprehension, eye-tracking technology has been used to study peoples' patterns of graph inspection while reading and interpreting graphs (e.g., Carpenter & Shah, 1998; Peebles & Cheng, 2003). Two studies used eye-tracking technology to compare experts to novices. In an early study, Vonder Embse (1987) compared experts and novices in mathematics as they read mathematical graphs. Results demonstrated that the experts fixated significantly longer on important parts of the graphs than did novices. These differences were associated with comprehension of the graphs: Experts performed better in a performance task measuring understanding of the graphs than did novices.

In a more recent study, Okan, Galesic and Garcia-Retamero (2016) also compared "experts" and "novices", however, in this study expertise was defined in terms of graph literacy skills (i.e., general knowledge about graphed data). More specifically, the researchers compared participants with low and high graph literacy while the participants interpreted health-related graphs. The researchers found that participants with high graph literacy devoted more time viewing the relevant features of the graph, whereas participants with low graph literacy focused more often on misleading graph features and misinterpreted the data presented by the graphs.

In sum, results of these two studies fit with results of eye-tracking studies in other fields: Compared to novices, experts tend to focus more on the task-relevant aspects of the graph, that is, the parts that are important for reading and interpreting graphs.

Eye Tracking and CBM Graph Comprehension

To the best of our knowledge, the present study is the first study that has employed eye-tracking technology to examine peoples' graph inspection patterns while reading and interpreting CBM graphs. Examining teachers' patterns of CBM graph inspection is important because it can contribute to the overall understanding of teachers' ability to comprehend CBM graphs. Whereas think-aloud data reveal what participants are thinking about when reading and interpreting the graphs (i.e., the content), eye-tracking data can provide additional insight into the visual approaches participants use to inspect the graphs (i.e., what elements they look at and in which order). Given that there are no previous studies focusing on teachers' eye movements while inspecting CBM graphs, we felt it was important to have a frame of reference for interpreting the teachers' data. Therefore, think-aloud and eye-tracking data also were collected from one CBM expert who completed the same tasks as the teachers.

Purpose of the Study

The present study was an exploratory, descriptive study, designed to examine how teachers visually inspect CBM graphs. The goals of the study were to examine: (1) how long teachers looked at the various elements of CBM graphs, and (2) whether teachers inspected those elements in a logical sequence. Data from one CBM expert are presented to provide a frame of reference for interpreting the teachers' data. As described earlier, this study was part of a larger study on teachers' comprehension of CBM graphs in which both think-aloud and eye-tracking data were collected. The results of the think-aloud portion of the study have been reported elsewhere (van den Bosch et al., 2017). The present paper focuses on the eye-tracking portion of the study.

METHOD

Participants

Teachers

Participants were 17 fifth- and sixth-grade teachers (15 female, 2 male; M_{age} = 42.9 years, *SD* = 11.77, range 26-60) from eight different schools in the Netherlands, and were recruited via convenience sampling. All teachers had completed a teacher education program and held bachelor's degrees in education. One teacher also held a master's degree in psychology. On average the teachers had 17.82 years (*SD* = 10.11, range 5-37) of teaching experience. All teachers had students with reading difficulties/dyslexia in their classes.

The original sample consisted of 23 teachers (19 elementary- and 4 secondary-school teachers). For purposes of the eye-tracking portion of the study, only data for the elementary-school teachers were included. In addition, data for two teachers were excluded because they completed a University course on CBM taught by the CBM expert included in this study.

Although familiar with progress monitoring in general (i.e., by using the data of standardized tests that are administered once or twice a school year), most teachers were not familiar with CBM progress-monitoring; that is, 16 of the 17 teachers reported that they had never heard of CBM. The one teacher that had heard of CBM had never implemented CBM nor received specific training in CBM. Thus, all teachers in the final sample were new to CBM.

CBM expert

As was done in the Wagner et al. (2017) study, expert data was included to provide a frame of reference for interpreting the teachers' data. Unfortunately, no eye-tracking data were collected from the three CBM experts who were included in the Wagner et al. study and served as a frame of reference for interpreting the teachers' think-aloud data (van den Bosch et al., 2017). To provide a frame of reference for interpreting the teachers' eye-tracking data, we thus included data from a different CBM expert.

The CBM expert included in the present study was a University professor in the area of learning disabilities, and held a Ph.D. in educational psychology/special education. The CBM expert had more than 23 years of experience conducting research and training on CBM, had published more than 45 articles, book chapters, and other documents on the topics of CBM and/or reading, and had given numerous presentations and workshops on CBM. It should, however, be noted that the CBM expert is the second author on the present paper. The CBM expert completed the tasks prior to the data collection, coding, and analysis of the teachers' data, but was aware of the goals of the study.

Given that there was only one CBM expert, and the fact the expert was an author on the paper, it was important to examine the extent to which the think-aloud data from the CBM expert in this study were similar to the think-aloud data from the CBM experts in the Wagner et al. (2017) study. The graphs used across studies were nearly the same (see following section), allowing for comparison. The comparison revealed that the think-alouds from the CBM expert in this study were similar to those of the CBM experts from the Wagner et al. study in terms of accuracy (100% for all four experts), completeness (9 out of 9 graph elements mentioned for our expert and 9, 8, and 8 graph elements mentioned for the other three experts), and sequential coherence (85% for our expert and 80%, 100%, and 75% for the other three experts; data reported in Wagner et al., 2017). With regard to the number of data-to-data, data-to-goal, and data-to-instruction comparisons/links our expert made more of these comparisons/links (21) than did the other three experts (12.5, 13.5, and 16); however, all four experts had made many more comparisons/links than did the teachers (4.5; data reported in van den Bosch et al., 2017).

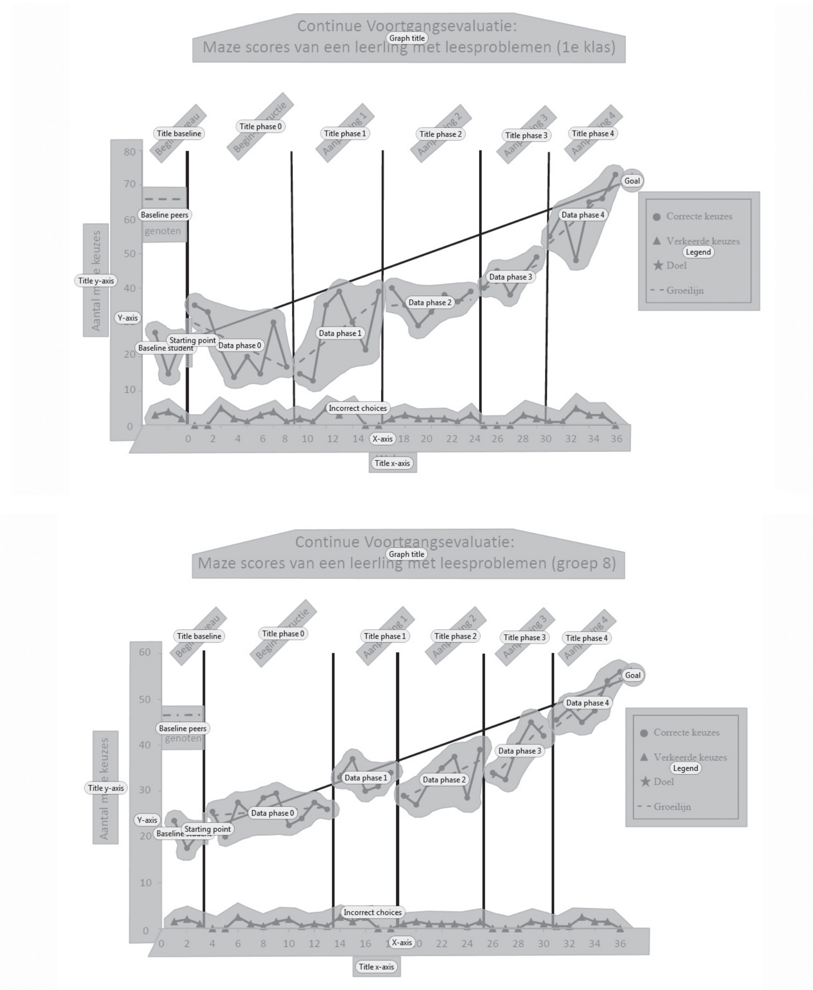

Figure 4.1. CBM graphs used in this study with the following AOIs (as depicted by the light grey areas): *Framing* (i.e., graph title, titles axes, x- and y-axis, legend), *Baseline* (i.e., title, data student, data peers), *Starting point* (beginning point goal line), *Instructional phases 0-4* (i.e., titles and data), *Incorrect choices* (triangles at bottom of graph), and *Long-range goal* (ending point goal line). Figure adapted from Wagner et al. (2017; used with permission).

Materials: CBM Graphs

The two researcher-made CBM graphs used in this study depicted fictitious but realistic student data (see Figure 4.1; note that the light grey areas on the graphs represent the Areas of Interest [AOIs; see Coding of the Eye-tracking Data section] and were not shown to the participants). Each graph included a legend, baseline data for the student and peers, a long-range goal, a goal line, and five phases of instruction, each with data points and a slope line. The data points and data patterns differed across the two graphs. The order in which the graphs were presented was counterbalanced (AB vs. BA) across teachers.

The graphs were slightly modified versions of the graphs used by Wagner et al. (2017). The graph titles, scales, and labels were changed to reflect CBM maze-selection rather than reading-aloud scores. This was done because the progress-monitoring data that the teachers collected as part of the larger study were maze-selection data. In all other respects, the graphs were identical to those used in the Wagner et al. study.

Eye-tracking Procedures

To examine participants' patterns of graph inspection, participants' eye-movements were recorded as they described each of the two researcher-made graphs. Prior to describing the graphs, participants were shown a sample CBM graph and given a short description of the graph. They were told that the graph depicted the reading progress of one student that received intensive reading instruction, and that the scores on the graph represented the student's correct and incorrect choices on weekly administered 2-minute maze-selection probes. Each graph element was identified and described briefly (see van den Bosch et al., 2017, for this description).

Participants were then positioned in front of the eye-tracker screen. They were told that they would be shown a CBM graph and that they would be asked to "think out loud" while looking at the graph. They were asked to tell all they were seeing and thinking, including what they were looking at and why they were looking at it. After the calibration was completed, the instructions were repeated in summarized form, and the first graph was presented. After the participant had described the first graph, the graph was removed from the screen, the instructions were again briefly repeated, and then the other graph was presented. The task had no time limits.

Data were collected in individual sessions at the teachers' schools. For the CBM expert, data were collected at the University. All data were collected by two trained doctoral students and a trained research assistant. Two data collectors were present during each data collection session. One data collector operated the eye-tracker while the other instructed the participant and audio-taped the think-aloud. Instructions were read aloud from a script.

Eye-tracker Apparatus and Software

To register the eye movements of the participants, a Tobii T120 remote eye-tracker was used. The Tobii T120 Eye Tracker is robust with regard to participants' head movements and its' calibration procedure is quick and simple (Tobii Technology, 2010). Participants were positioned in front of the Tobii eye-tracker screen so that the distance between their eyes and the screen was approximately 60 cm. The data sampling rate was set at 60 Hz. The accuracy of the Tobii T120 Eye Tracker typically is 0.5 degrees, which implies an average error of 0.5 centimeter between the measured and the actual gaze direction (Tobii Technology, 2010). Tobii Studio 3.4.8 and IBM SPSS Statistics 23 were used to process and to descriptively analyze the eye-tracking data.

Coding of Eye-tracking Data

Establishing areas of interest

In order to analyze the eye-tracking data, ten areas of interest (AOIs) were defined for each of the two graphs, corresponding to the various elements of each CBM graph (see Figure 4.1). The AOIs were: *Framing* (elements related to the graph set-up, including titles, labels, the x- and y-axes, and the legend), *Baseline* (title of the baseline and baseline data from the student and the peers), *Starting point* (beginning point of the goal line), *Instructional phases 0 to 4* (titles and data from phases 0 to 4), *Incorrect choices* (represented by triangles at the bottom of graph), and *Long-range goal* (ending point of the goal line).

Fixation duration and fixation sequence

Two types of eye-tracking data were examined in this study: Fixation duration data and fixation sequence data. A *fixation* is defined as a short period of time in which the eyes remain still to perceive a stimulus, that is, to cognitively process the stimulus (Holmqvist et al., 2011). Fixations serve as a measure of visual attention. *Fixation duration* refers to the sum of the duration for all fixations within a particular area of the stimulus and *fixation sequence* refers to the order in which participants look at each of the areas. The minimal fixation duration setting was set to 200 ms, meaning that a fixation was not registered unless the participant looked at a specific point for at least 200 ms. This cutoff point was chosen because typical values for fixations range from 200-300 ms (Holmqvist et al., 2011).

Fixation duration

Fixation duration serves as an indicator of participants' distribution of visual attention. For each AOI, the total duration of fixations (in sec) was computed via the eye-tracker software. Then, the percentage of visual attention devoted to each AOI was calculated.

Fixation sequence

Fixation sequence referred to the order in which participants viewed the various graph elements (that were defined as AOIs). For each participant, the sequence of fixations was computed via the eye-tracker software. The fixation sequence data were provided in the form of strings of AOI names (e.g., *Baseline, Phase 1, Phase 2, Phase 1, etc.)*.

To determine the extent to which the sequences followed a logical order, we compared each sequence string to an "ideal" sequence and calculated a logical sequence percentage. The AOIs for the ideal sequence were similar to the content codes for the ideal sequence used to determine sequential coherence for the think-aloud data (van den Bosch et al., 2017; Espin et al., 2017; Wagner et al., 2017) with two exceptions (see Table 4.1). Recall that the ideal sequence represented the order in which CBM graphs are used for instructional decision-making.

Table 4.1. Definitions of the Think-aloud Codes and Corresponding Areas of Interest (AOIs)

Think-aloud Codes	**Definition**	**Corresponding AOIs**
Framing (FR)	Statements about the set-up of the graph and/or the measures that were used to obtain the data.	Graph title, title x-axis, title y-axis, x-axis, y-axis, legend
Baseline (BL)	Statements about the beginning level of performance of the student and/or the peers.	Title baseline, baseline student, baseline peers
Goal setting (GS)	Statements about setting the long-range goal based on the starting point and the expected rate of growth.	Starting point, long-range goal*
Instructional phase 0 (P0)	Statements about the scores, progress, and/or variability within instructional phase 0.	Title phase 0, data phase 0
Instructional phase 1 (P1)	Statements about the scores, progress, and/or variability within instructional phase 1.	Title phase 1, data phase 1
Instructional phase 2 (P2)	Statements about the scores, progress, and/or variability within instructional phase 2.	Title phase 2, data phase 2
Instructional phase 3 (P3)	Statements about the scores, progress, and/or variability within instructional phase 3.	Title phase 3, data phase 3
Instructional phase 4 (P4)	Statements about the scores, progress, and/or variability within instructional phase 4.	Title phase 4, data phase 4
Goal achievement (GA)	Statements about whether or not the student achieved the long-range goal.	Long-range goal*

Note. * If participants fixated on the long-range goal prior to fixating on any of the instructional phases, the fixation was coded under goal setting. If participants fixated on the long-range goal after fixating on at least one instructional phase, the fixation was coded as goal achievement.

The two exceptions concerned the AOIs "*Long-range goal*" and "*Incorrect choices*". With respect to the *Long-range goal*, participants might inspect the long-range goal either as a part of goal setting (to determine what the expected end level of performance was for the student) or as a part of goal achievement (to determine whether or not the student had achieved or would achieve the goal). Thus, the following coding rule was made for categorizing fixations on the long-range goal: If participants fixated on the long-range goal prior to fixating on any of the instructional phases, the fixation was coded under goal setting. If they fixated on the long-range goal after fixating on at least one instructional phase, the fixation was coded as goal achievement.

With respect to the *Incorrect choices*, in coding the think-aloud data, statements about the number of incorrect maze-selection choices (i.e., the triangles at the bottom of the graph) were coded as the instructional phase they referred to (van den Bosch et al., 2017; Espin et al, 2017; Wagner et al., 2017). In coding the eye-tracking data, we created one AOI for the incorrect choices of all five phases (see Figure 4.1) rather than separate AOIs for the incorrect choices within each phase. This was done because we were primarily interested in visual attention for the correct choices (and for the correct versus incorrect choices), as it is the number of correct choices that reflects progress (Deno, 1985). As a consequence, fixations on the incorrect choices could not be coded as the phase they "referred" to, and were, therefore, *not* included in the logical sequence coding.

To code the fixation sequence data, the coding sheet presented in Figure 4.2 was used. The ideal sequence was: *Framing* (i.e., fixating on the elements related to the set-up of the graph), *Baseline*, *Goal setting*, *Instructional phases 0 to 4*, and *Goal achievement*, and is depicted by the light grey boxes above the diagonal. Along the top and down the left side of the coding sheet, the graph elements are listed. Sequences between graph elements were recorded using tally marks. To illustrate, the fixation string presented earlier (*Baseline, Phase 1, Phase 2, Phase 1, etc.*) has been coded in Figure 4.2. To code the first sequence, Baseline (BL) to Phase 1 (P1), a tally mark was placed at the intersection of the BL row and the P1 column. To code the next sequence, Phase 1 (P1) to Phase 2 (P2), a tally mark was placed at the intersection of the P1 row and the P2 column. To code the last sequence, Phase 2 to Phase 1, a tally mark was placed at the intersection of the P2 row and P1 column. The outcome measure was the percentage of sequences following the ideal sequence. In the example, 1 of 3 sequences falls in the light grey boxes above the diagonal and follows the ideal sequence. Thus, the logical sequence percentage for this example is 33%.

When comparing the AOI strings to the ideal sequence, we observed that both the teachers and the CBM expert often looked back and forth between two adjacent graph elements, and in particular, between two adjacent instructional phases. Such looking back and forth might imply that participants were comparing the various graph elements/data to each other. In research on graph comprehension, such within-the-data comparisons are considered to be an important aspect of higher-level graph comprehension (Friel et al., 2001). We thus decided to also calculate the logical sequence percentages in a second, more liberal way, in which we included instances of looking back and forth between two adjacent graph elements (as depicted by the light grey boxes just *above and* just *below* the diagonal in Figure 4.2) as part of the ideal sequence. In the example provided earlier, 2 of 3 sequences fall in the light grey boxes above and below the diagonal. Thus, the logical sequence percentage using the liberal calculation approach would be 66%, whereas it was 33% using the original (referred to as strict) calculation approach. In addition, to quantify the observation that participants often looked back and forth between adjacent instructional phases, we calculated the percentage of sequences between adjacent phases.

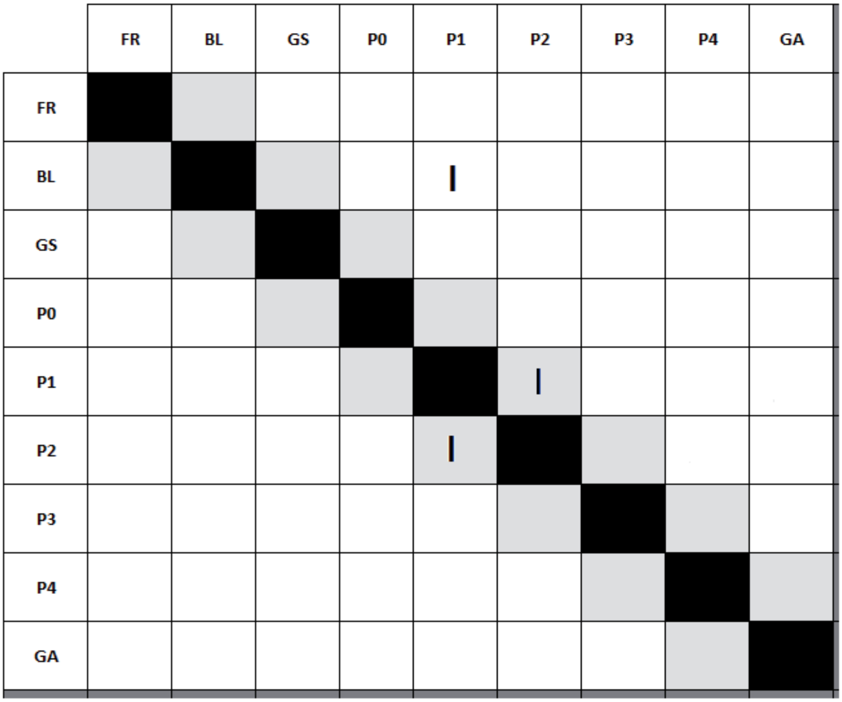

Figure 4.2. Coding sheet for calculating the logical sequence percentages from the fixation sequence data. Two approaches were used to calculate those percentages. For the first approach, referred to as the strict calculation approach, the light grey boxes *above* the diagonal represent the ideal sequence and the number of tally marks within these boxes is the numerator (1 in this example). For the second approach, referred to as the liberal calculation approach, the light grey boxes *above and below* the diagonal represent the ideal sequence and the number of tally marks within these boxes is the numerator (2 in this example). For both approaches, the total number of tally marks in the sheet is the denominator. FR = Framing; BL = Baseline, GS = Goal setting, P0 = Instructional phase 0, P1 = Instructional phase 1, P2 = Instructional phase 2, P3 = Instructional phase 3, P4 = Instructional phase 4, GA = Goal achievement. Figure adapted from Espin et al. (2017; used with permission).

Intercoder agreement

The fixation sequence data for all participants were coded by a trained doctoral student and a trained research assistant. Agreement was 99.94%. The only one disagreement between coders was resolved through discussion.

General Procedures

Prior to the beginning of the study, permission was obtained from the Human Subjects Review Board and informed consent was obtained from all participants. As part of the larger study, teachers first collected weekly CBM maze-selection data to monitor the progress of two of their students with reading difficulties/dyslexia over a period of 10 to 12 weeks. Note that the maze-selection data were collected and graphed via an online progress-monitoring system. Next, teachers completed a graph-reading skills test and provided information on their graph-reading experience. Teachers then completed the think-aloud/eye-tracking task for the two researcher-made graphs, and, then, for the two student graphs. Recall that the CBM expert completed the think-aloud/eye-tracking task prior to the collection, coding, and analysis of the teachers' data, and completed the task for the researcher-made graphs only.

RESULTS

Fixation Duration

With regard to the first goal of the study, that is, to examine how long teachers looked at the various elements of CBM graphs, we first present data on the overall viewing time and, then, present more specific data on the fixation duration for the various graph elements for both the teachers and the CBM expert. Data are reported as average scores across the two graphs.

The mean overall viewing time for the teachers was 107.91 seconds per graph (*SD* = 59.83; range 53-252.5), and for the CBM expert it was 283 seconds per graph.

The percentages of visual attention (i.e., fixation duration) devoted to each graph element for both the teachers and the CBM expert are reported in Table 4.2, and presented visually in the top panel of Figure 4.3. The data reveal that both the teachers and the CBM expert devoted the majority of visual attention to the instructional phases (labeled Instructional Phases 0-4 in Table 4.2), although the percentage was smaller for teachers (58%) than for the CBM expert (70%). Examination of the individual phases reveals that teachers devoted relatively *more* attention to initial instruction (Phase 0) than did the CBM expert (12% vs. 3%), and relatively *less* attention to later instructional phases (Phases 3 and 4) than did the CBM expert (7% vs. 16% and 13% vs. 25% respectively). Both the teachers and the CBM expert devoted a fair amount of visual attention to framing, although the percentage was larger for teachers (26%) than for the CBM expert (23%). Finally, teachers devoted a larger percentage of visual attention to the baseline data and to the incorrect choices than did the CBM expert (7% vs. 4% and 7% vs. 0% respectively).

Table 4.2. Mean Percentages of Visual Attention Devoted to the Graph Elements for the CBM Expert, all Teachers, and the HQ-TA and LQ-TA Teachers

	CBM Expert (*N* = 1)	All teachers (*N* = 17)	HQ-TA teachers (*n* = 2)	LQ-TA teachers (*n* = 2)
Graph elements				
- Framing (graph title, titles axes, axes, legend)	22.66	25.61 (10.54)	17.27	27.08
- Baseline (title, data student, data peers)	3.70	7.42 (4.31)	6.22	12.06
- Starting point	0.56	0.46 (0.93)	0	0.20
- Instructional phase 0 (title, data)	2.57	12.48 (6.81)	8.94	9.57
- Instructional phase 1 (title, data)	13.23	13.81 (4.21)	15.97	9.19
- Instructional phase 2 (title, data)	13.52	11.23 (3.82)	12.58	12.86
- Instructional phase 3 (title, data)	15.68	6.99 (2.79)	10.88	3.19
- Instructional phase 4 (title, data)	24.59	13.04 (6.27)	17.72	13.2
- Instructional phases 0-4 (titles, data)	69.59	57.55 (9.39)	66.09	48.02
- Long-range goal	3.27	2.07 (2.16)	1.92	2.04
- Incorrect choices	0.22	6.89 (4.52)	8.49	10.61

Note. In the "All teachers column", standard deviations are provided in parentheses. HQ-TA teachers = teachers with high-quality think-alouds, LQ-TA teachers = teachers with low-quality think-alouds.

Variability between teachers

Although results revealed some differences between teachers and the CBM expert in the distribution of visual attention across various graph elements, there was a fair amount of variability within the teachers' data (see *SD's* in Table 4.2). To gain more insight into the between-teacher variability, we compared the eye-tracking data for the two teachers with the highest-quality think-alouds and the two teachers with the lowest quality think-alouds to the eye-tracking data for the CBM expert.

To identify the teachers with high- and low-quality think-alouds, we examined the teachers' scores on the following aspects of the think-alouds (see van den Bosch et al., 2017): Accuracy, completeness, sequential coherence, data-to-data comparisons, data-to-goal comparisons, and data-to-instruction links. For each aspect, we rank-ordered teachers from highest to lowest and assigned ranking numbers (e.g., 1 for the highest ranking, 2 for the next highest ranking, etc.). We then summed the rankings across all six aspects, and identified the two teachers with the lowest rankings and the two teachers with the highest rankings.

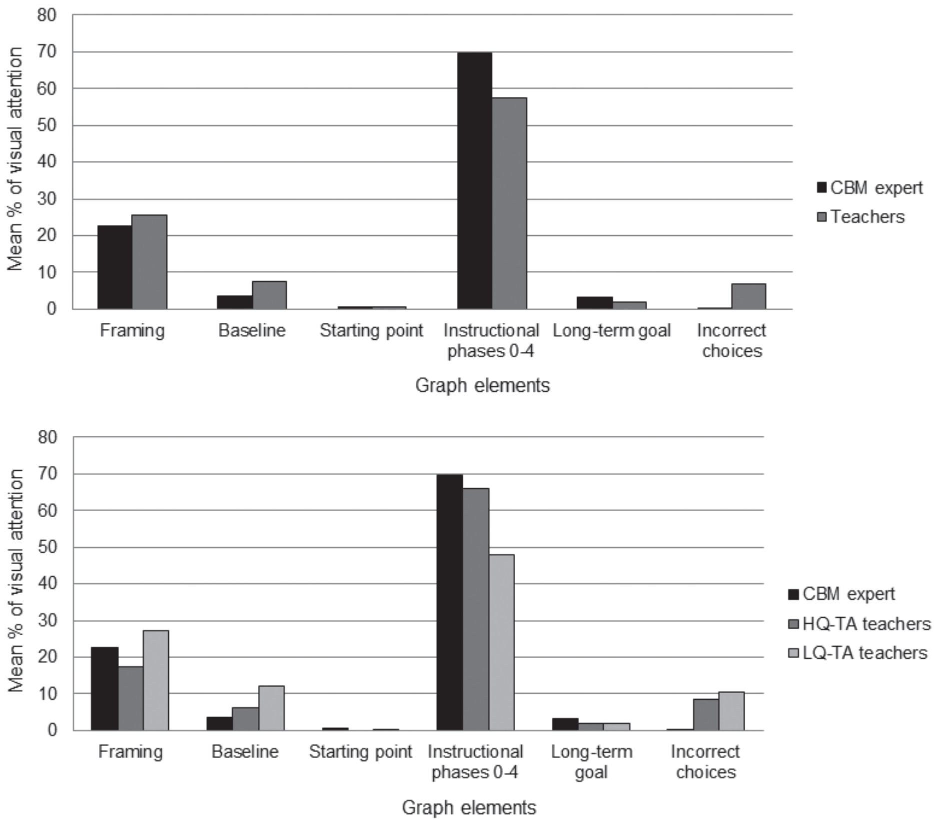

Figure 4.3. Mean percentages of visual attention devoted to the various graph elements for the CBM expert and the teachers (top panel), and for the CBM expert and the HQ-TA and LQ-TA teachers (bottom panel). Note that the data that are presented for the CBM expert are the same data in both panels. HQ-TA teachers = teachers with high-quality think-alouds, LQ-TA teachers = teachers with low-quality think-alouds.

The visual attention data for the two teachers with high-quality think alouds (HQ-TA teachers) and the two teachers with low-quality think-alouds (LQ-TA teachers) are reported in the last two columns of Table 4.2, and presented visually in the bottom panel of Figure 4.3. Perhaps most notable is the fact the HQ-TA teachers devoted nearly as much visual attention to the instructional phases as the CBM expert (66% vs. 70%). LQ-TA teachers, on the other hand, devoted far less attention to the instructional phases, only 48%. Also of note is the visual attention devoted to incorrect choices. Both the HQ-TA teachers and the LQ-TA teachers devoted more attention to incorrect choices than the CBM expert (8 and 11% vs. 0%). Finally, differences in visual attention devoted to framing also were seen, with HQ-TA teachers devoting less visual attention to framing than LQ-TA teachers (17% vs. 27%), compared to 23% for the CBM expert.

Fixation Sequence

With regard to the second goal of the study, that is, to examine whether teachers inspected the various graph elements in a logical sequence, we present the logical sequence percentages (as calculated by using both calculation approaches) for the teachers and the CBM expert. In addition, we present the percentages of sequences between adjacent instructional phases.

Using the strict calculation approach, the mean logical sequence percentage for teachers was 24.59% (*SD* = 5.96, range 15.78-37.50). This was compared to a logical sequence percentage of 40.83% for the CBM expert. Using the liberal calculation approach, the mean logical sequence percentage for the teachers was 40% (*SD* = 10.8, range 18.16-56.49), compared to a logical sequence percentage of 74.11% for the CBM expert. The mean percentage of sequences between adjacent instructional phases for the teachers was 30.44% (*SD* = 9.7), compared to 49.62% for the CBM expert.

Variability between teachers

As with the visual attention data, we compared the fixation sequence data for the two HQ-TA and two LQ-TA teachers to data for the CBM expert. Using the strict calculation approach, the mean logical sequence percentages for the HQ-TA and LQ-TA teachers were 33.57% and 16.94%, respectively, compared to 40.83% for the CBM expert. Using the liberal calculation approach, the mean logical sequence percentages for the HQ-TA and LQ-TA teachers were 50.39% and 30.19%, respectively, compared to 74.11% for the CBM expert. The mean percentages of sequences between adjacent instructional phases for the HQ-TA and LQ-TA teachers were 37.75% and 18.13%, respectively, compared to 49.62% for the CBM expert. Thus, like for the visual attention data, for the fixation sequence data the percentages for the HQ-TA teachers were also closer to those of the CBM expert than were the percentages for the LQ-TA teachers.

DISCUSSION

The purpose of the present study was to examine how teachers visually inspect CBM graphs. More specifically, our goals were to examine: (1) how long teachers looked at the various elements of CBM graphs while inspecting and describing the graphs, and (2) whether teachers inspected those graph elements in a logical sequence. To provide a frame of reference for interpreting the teachers' data, we also presented data from a CBM expert.

Fixation Duration

With regard to the first goal of the study, we first examined the overall viewing time. The overall viewing time per graph for the teachers was about 2.5 times shorter than that for the CBM expert. Given that the task had no time limits, this difference might imply that the teachers were sooner satisfied with their inspection and description of the CBM graphs. This result might reflect the fact that teachers did not exactly know what to look for in the graphs or did not know how to describe the graphs, and, therefore, inspected and described the graphs in a less detailed way than the CBM expert. Next, we examined how the participants distributed their visual attention across the various graph elements.

One notable finding was that the teachers devoted the majority of their visual attention (58%) to the data in the instructional phases, thus, to the parts of CBM graphs that were most relevant for instructional decision-making. The next highest category was framing, implying that the teachers also devoted a fair amount of attention to graph elements that provide a context for the data. It should, however, be pointed out that the AOIs mainly included data in the instructional phases and graph elements that provide a context for the data.

It is vital that teachers devote considerable time to the data in the instructional phases. That is, to make sound data-based instructional decisions, teachers have to inspect the data thoroughly to be able to draw conclusions about student progress and the effectiveness of instruction. However, despite the fact that the majority of teachers' visual attention was devoted to those data, there was a discrepancy between the teachers and the CBM expert with regard to the percentage of visual attention devoted to the data in the instructional phases (58% vs. 70%). This discrepancy might reflect the fact that the CBM expert better knew what graph elements or what data to look at than did the teachers. This explanation fits well with previous eye-tracking studies comparing experts and novices showing that experts focus on aspects of the visual stimuli that are relevant within the context of the task and skim over less relevant aspects (e.g., Al-Moteri et al., 2017; Canham & Hegarty, 2010; Gegenfurthner et al., 2011; Jarodzka et al., 2010; Okan et al., 2016; Vonder Embse, 1987).

Moreover, in this study, the teachers devoted more visual attention to the incorrect choices – that is, to an irrelevant part of CBM graphs – than did the CBM expert, who did not pay any attention to the incorrect choices. The teachers might have spent more time inspecting incorrect choices because they might not have known it is the number of correct, not the number of incorrect, choices that reflects progress in the context of CBM. Another reason might be that teachers might have the tendency to focus on students' errors.

Fixation Sequence

With regard to the second goal of the study, we examined whether teachers inspected the various elements of CBM graphs in a logical sequence, that is, in the order in which CBM graphs are used for instructional decision-making. Results revealed that teachers inspected the CBM graphs in a less logical sequence than the CBM expert: For the teachers, 25% of the sequences between graph elements followed the ideal sequence, whereas for the CBM expert 41% of the sequences followed the ideal sequence. When calculating the logical sequence percentages in a second, more liberal way, the same pattern of results was found. These results are in line with previous eye-tracking studies comparing experts and novices, showing that experts are more systematic and goal-directed in completing a visual task than novices (e.g., Al-Moteri et al., 2017; Jarodzka et al., 2010). Moreover, these results also fit well with previous think-aloud studies on CBM graph comprehension, showing that CBM experts describe CBM graphs in a more logical, sequential manner than preservice and inservice teachers (van den Bosch et al., 2017; Espin et al., 2017; Wagner et al., 2017).

In addition to the sequence in which participants inspected the various elements of CBM graphs, we also examined the percentage of sequences between adjacent instructional phases to quantify the observation that participants often looked back and forth between adjacent instructional phases. Results revealed that this percentage was smaller for the teachers than for the CBM expert. That is, for the teachers 30% of the sequences were sequences between adjacent instructional phases, whereas for the CBM expert 50% of the sequences were sequences between adjacent instructional phases, suggesting that the teachers less often compared the data points or slope lines across adjacent instructional phases than did the CBM expert. Given that such within-the-data comparisons are considered to be an important aspect of higher-level graph comprehension (Friel et al., 2001), those results imply that the teachers comprehended the CBM graphs less well than the CBM expert.

In sum, both the fixation duration and the fixation sequence data demonstrated that teachers' graph inspection patterns differed from that of the CBM expert. That is, as a group, the teachers devoted less visual attention to important elements of the graphs and inspected the graph elements in a less logical sequence than did the CBM expert. For both the fixation duration and the fixation sequence data, there was, however, a fair amount of between-teacher variability.

Variability Between Teachers

To gain more insight into the between-teacher variability, we compared the data for the two teachers with high-quality think-alouds (HQ-TA teachers) and the two teachers with low-quality think-alouds (LQ-TA teachers) to data for the CBM expert. Overall, this comparison revealed that the graph inspection patterns for the HQ-TA teachers were more similar to that of the CBM expert than were graph inspection patterns for the LQ-TA teachers.

More specifically, with regard to the fixation duration data, the HQ-TA teachers devoted nearly as much visual attention to the data in the instructional phases as did the CBM expert (66% vs. 70%), whereas the LQ-TA teachers devoted far less attention to the data in the instructional phases (48%). This is an important difference because the data in the instructional phases provide the necessary information for CBM instructional decision-making. The LQ-TA teachers not only devoted less visual attention to the relevant aspects of CBM graphs than did the HQ-TA teachers and the CBM expert, they also devoted relatively more visual attention to the incorrect choices, that is, to a less relevant aspect of the graphs.

With regard to the fixation sequence data, the HQ-TA teachers inspected the various graph elements in a less logical sequence and looked back and forth less often between adjacent instructional phases than did the CBM expert (34% vs. 41% and 38% vs. 50%, respectively), and the LQ-TA teachers inspected the graph elements in a far less logical sequence and looked back and forth far less often between adjacent instructional phases than did the CBM expert (17% vs. 41% and 18% vs. 50%, respectively). However, although the logical sequence percentages and the percentage of sequences between adjacent instructional phases of the HQ-TA teachers were closer to that of the CBM expert, the differences between these teachers and the CBM expert were still substantial.

In sum, the data for the HQ-TA and LQ-TA teachers showed that the HQ-TA teachers were better able to identify the relevant parts of the CBM graphs than were the LQ-TA teachers; however, both the HQ-TA and LQ-TA teachers devoted more attention to the incorrect choices (that are less relevant) than did the CBM expert, who did not pay any attention to the incorrect choices. Second, the data showed that the HQ-TA teachers inspected the graph elements in a more logical sequence and more often compared the data across adjacent instructional phases than did the LQ-TA teachers; however both the HQ-TA and LQ-TA teachers did this less well than did the CBM expert. Thus, for all teachers there was room for improvement.

Limitations and Directions for Future Studies

The present study was the first study to examine teachers' inspection patterns of CBM graphs using eye-tracking technology. Given that it was an exploratory study, the results should be replicated in future studies with larger and more diverse research groups.

One limitation of the study was that teachers were recruited via convenience sampling. In addition, the sample size was small (but appropriate for an exploratory study). Another limitation was that only one CBM expert was included as a frame of reference for interpreting the teachers' eye-tracking data, and that this expert was also an author on the present paper. The fact that the CBM expert's think-aloud data were similar to the think-aloud data from the CBM experts from the Wagner et al. (2017)/van den Bosch et al. (2017) studies and that the CBM expert completed the tasks prior to the data collection, coding, and analysis of the teachers' data, lends credibility to the results, but replication with other CBM experts is needed.

An important next step in studying teachers' CBM graph comprehension is to examine the relation between teachers' graph inspection patterns and their use of CBM data for instructional decision-making, and the resulting effects on student achievement.

Implications for Practice

Although teachers are expected to closely monitor the progress of students with severe and persistent learning difficulties and to evaluate the effectiveness of the given instruction for those students with systems like CBM, the results of the present study have demonstrated that teachers have difficulties with inspecting CBM graphs. Together with the results of the previous think-aloud studies (van den Bosch et al., 2017; Espin et al., 2017; Wagner et al., 2017), the results of this study call for a need to teach teachers how to inspect, read, and interpret CBM graphs. Providing teachers with CBM training seems particularly warranted given that research demonstrates that student achievement only improves when teachers adequately respond to CBM data with instructional or goal changes (see Stecker, Fuchs, & Fuchs, 2005, for a review).

In CBM training, teachers might benefit from explicit instruction about how to inspect, read, and interpret the graphs. One simple instructional recommendation could be, for example, that teachers not pay attention to incorrect choices because incorrect choices are less relevant than correct choices for CBM instructional decision-making. Another option would be to provide teachers with instruction about where to pay attention while inspecting, reading, and interpreting CBM graphs. Keller and Junghans (2011) have examined whether visual attention for task-relevant parts is a teachable skill, and have demonstrated that providing viewers with written instructions on graph reading and with arrows pointing to the task-relevant parts of medical graphs lead to increased visual attention for these task-relevant graph parts. Providing spoken instructions on how to inspect, read, and interpret CBM graphs while highlighting the graph elements that are mentioned might also be an effective training strategy, given that the combination of verbal and visual input leads to better comprehension (Sadoski & Paivio, 2004).

A different approach to provide teachers with attentional guidance with regard to inspecting CBM graphs, as suggested by Jarodzka et al. (2010) in the context of their expert/novice study in the area of fish locomotion, is to use videos of experts' eye movements with cued verbalizations as training materials. With regard to the present study, teachers could be shown a video of the think-aloud and eye movements of a CBM expert to illustrate how to inspect the graph in a more detailed, and in a logical, sequential manner.

Conclusion

The results of this exploratory, descriptive study provide insights into how teachers' visually inspect CBM progress graphs. Differences were found with regard to how long the teachers and the CBM expert looked at the various graph elements and with regard to the order in which they inspected those graph elements. For both aspects, it appeared that the graph inspection patterns of the teachers with HQ-TA were more similar to the graph inspection patterns of the CBM expert than those of the LQ-TA teachers. That is, the HQ-TA teachers were better able to identify the relevant parts of the CBM graphs, inspected the various graph elements in a more logical sequence, and more often compared data across adjacent instructional phases than did the LQ-TA teachers. However, both the HQ-TA and LQ-TA teachers inspected the graphs less well than did the CBM expert, suggesting that both the HQ-TA and LQ-TA teachers might benefit from CBM training. If the results of this study were to be replicated in future studies, they would provide important information with regard to teaching teachers to inspect, read, interpret, and use CBM data for instructional decision-making.