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Do seductive details do their damage in the context of graph comprehension? Insights from eye movements

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Summary

In educational research, interesting but irrelevant materials are often considered seductive details, which are suspected to have detrimental effects on learning. Although seductive details have been mostly examined in the context of text comprehension, such elements are also used in graphs (e.g., depicting data points). In the present experiment, we investigated both seductive text and seductive pictures in the context of graph comprehension as well as the interaction of seductive details with spatial working memory capacity (SWMC). We recorded N = 68 students' eye movements, while they analyzed bar graphs in a within-subject design. Data were analyzed with linear mixed-effects models. Results show that seductive details did not affect students' graph reading performance but prolonged the task processing time. Eye-fixation measures revealed that additional processing time was best explained by attention distraction towards the seductive material. SWMC did not affect the presence or the extent of the seductive details effect.

KEYWORDS

distraction and disruption, eye tracking, graph comprehension, linear mixed-effects models, seductive details effect

1 | INTRODUCTION

Computer-based learning and testing make it easy to enrich educational material with additional multimedia content. To describe information that is task irrelevant but perceived as interesting for learners and therefore used by instructors to spice up educational material, Garner, Brown, Sanders, and Menke (1992) and Garner, Gillingham, and White (1989) coined the term seductive details. Harp and Mayer (1997, 1998) further distinguished between *seductive text* to describe interesting but irrelevant text and *seductive illustrations* to describe interesting but irrelevant pictures.

Although there is evidence that additional but irrelevant material may increase student interest (cf. Harp & Mayer, 1997; Lenzner, Schnotz, & Müller, 2013), seductive details are also known for their detrimental effects on retention and transfer in learning (e.g., Harp & Mayer, 1997; Lehman, Schraw, McCrudden, & Hartley, 2007; Rowland-Bryant et al., 2009). Typically, researchers have examined the *seductive details effect* in the context of text comprehension (e.g., Mayer, Griffith, Jurkowitz, & Rothman, 2008; Rey, 2011), whereas research on graph comprehension was mainly concerned with visual features that are part of the graphical system (e.g., legends, data complexity, size, position, and more; Cleveland & McGill, 1987; Kim & Lombardino, 2015; Kumar & Benbasat, 2004; Shah & Hoeffner, 2002). However, digital media such as presentations, websites, and computer-based learning material provide accessible ways to supplement graphs in the same ways as text (e.g., depicting the content of data points or providing additional information). There are reasons to assume that seductive details may affect graph comprehension as well. By design, graphs are highly conventionalized visual systems in which spatial relations between visual objects are employed as an analogy to non-spatial relations (Schnotz, 2002; Winn, 1990). Thus, extraneous material may be distracting and disruptive for the process of graph reading that relies on the structural conventions and spatial analogies employed in graphs.

Furthermore, seductive text and seductive pictures may affect the comprehension process differently, because text and pictures belong to structurally different types of representations. According to Schnotz (2001), text and spoken words are descriptive representations, whereas pictures are depictive representations. Descriptive representations on the one hand consist of symbols that have an arbitrary structure and are related to the content they represent only by means of convention. Depictive representations on the other hand are iconic representations that represent the associated content through common structural characteristics (e.g., Schnotz, 2001; Schnotz & Bannert, 2003). Schnotz and Bannert (2003) argue that descriptive and depictive representations produce different internal mental representations and are processed in different cognitive branches when students build a mental model of the learning material.

Theoretical explanations for the seductive details effect are linked to the fact that working memory capacity (WMC) is limited (Baddeley & Hitch, 1974) and can easily be overloaded by extraneous material (i.e., extraneous cognitive load; see, e.g., Paas & Sweller, 2014). For example, Sanchez and Wiley (2006) found that individuals with low WMC were especially vulnerable to the seductive details effect as they were less able to direct their attention towards the relevant information. A number of underlying mechanisms have been proposed (Harp & Mayer, 1998), but a meta-analysis by Rey (2012) showed overall mixed results as to how the seductive details effect is caused.

In the present experiment, we integrated the two types of seductive material into various graph comprehension tasks—seductive text and seductive illustrations—and investigated how these additional materials would affect students' error rate and processing time while accounting for individual differences in WMC. In addition, we aimed to gain deeper insights into the processes that take place during the solution of graph tasks with and without seductive materials. Therefore, we applied eye tracking methodology, which has proven useful in previous graph comprehension studies (e.g., Kim & Lombardino, 2015; Peebles & Cheng, 2003; Strobel, Saß, Lindner, & Köller, 2016).

2 | THE SEDUCTIVE DETAILS EFFECT

In educational research, seductive details are described as interesting but irrelevant details related to a given topic but not necessary to achieve the instructional objective (Harp & Mayer, 1998; Mayer & Fiore, 2014). To introduce a classic example, Harp and Mayer (1997) used an educational text on lightning formation. In this paradigmatic approach, a story about a football player who got struck by lightning and corresponding illustrations were added to the informational text about the genesis of lightning. Even though the additional material has topical relevance (i.e., it is related to the topic of lightning), it has little conceptual relevance (i.e., it is not related to the instructional objective: learning the process of lightning formation; Mayer, 2009). Results across multiple studies consistently revealed that adding seductive details to an informational passage had detrimental effects on retention of important information (e.g., Doolittle & Altstaedter, 2009; Lehman et al., 2007). Typically, students remembered less of the main ideas of the text and more of the seductive details (for a meta-analysis on seductive details, see Rey, 2012). However, it should be noted that decorative pictures may foster learning and retention under specific circumstances; for example, if they trigger anthropomorphism (Schneider, Nebel, Beege, & Rey, 2018).

In the context of graph comprehension, seductive details may interfere with the graph reading process as the extraneous elements and the structural important graph elements compete for a reader's limited cognitive capacity (see, e.g., Mayer & Fiore, 2014; Paas & Sweller, 2014).

Harp and Mayer (1998) postulate three potential causes of the seductive details effect that adhere to cognitive load theory (Paas & Sweller, 2014; Sweller, 1994): distraction, disruption, and diversion. According to the *distraction hypothesis*, seductive details divert a reader's attention away from the relevant information and towards the more interesting but irrelevant information. As a result, readers my select and retain information that is not relevant to the task. The *disruption hypothesis* suggests that seductive details interrupt the transition "from one main idea to the next" (Harp & Mayer, 1998, p. 415). In other words, the reading process is interrupted so that readers have to revisit previously inspected passages in order to continue were they left off (Sanchez & Wiley, 2006). This way the mental model construction process (e.g., Schnotz, 2002) is complicated and may result in incomplete or incoherent representations. Finally, the *diversion hypothesis* attributes the detrimental effects of seductive details to the activation of inappropriate representations: Although readers are still able to construct a coherent mental model, they are not building their representation around the important information in the text. Instead, seductive details encourage the activation of inappropriate prior knowledge, leading to a mental model construction around the irrelevant information.

Although Harp and Mayer (1998) found some evidence in favor of the diversion hypothesis, more recent studies challenged this notion. Presenting seductive material before a text instead of embedding it within the text has shown to mitigate the seductive details effect (e.g., Wiley, 2003; Wright, Milroy, & Lickorish, 1999). If poorer comprehension due to seductive material was caused by diversion, the position of the seductive material should have no effect on students' learning performance. These findings suggest that interference is somehow involved in the mechanism of the seductive details effect, highlighting the role of distraction and disruption.

Sanchez and Wiley (2006) argue that both distraction and disruption are related to low WMC. In their study on the relationship between seductive details and working memory, they found that WMC affected learning outcomes only when seductive details were present in the material. More precisely, the effect was most evident in the group of students with low WMC, showing that these readers were especially vulnerable to the seductive details effect.

The authors conclude that individuals with lower WMC were less able to deal with distracting information and irrelevant material and consequently focused less on the relevant conceptual information.

3 | SEDUCTIVE DETAILS IN THE CONTEXT OF GRAPH COMPREHENSION

Traditionally, researchers have examined the seductive details effect in the context of learning, often associated with text comprehension and the recall of important information (e.g., Garner et al., 1989; Lehman et al., 2007). With this study, we apply the research on learning with seductive details to graph reading tasks and immediate performance. This implies tackling two challenges.

First, we expand the traditional research on seductive details to the area of graph comprehension. Research on graph comprehension is often concerned with computational differences between various graph types (e.g., Peebles & Cheng, 2003; Pinker, 1990; Shah & Hoeffner, 2002; Shah, Mayer, & Hegarty, 1999), between graphs and other representations (e.g., Wainer, 1992), as well as visual features that affect graph comprehension and learning with graphs (e.g., color, position, size, legends, data complexity, and more; Cleveland & McGill, 1987; Kim & Lombardino, 2015; Kumar & Benbasat, 2004; Shah & Hoeffner, 2002). Although there has been no research on irrelevant but interesting details in graphs, there are findings on irrelevant data. For example, Kim and Lombardino (2015) conducted an eye tracking study and varied the number of data series presented in bar graphs. They found that processing time was significantly higher when an additional data series was present. This was also reflected in longer eye-fixation times on the graph regions. However, graphs are highly conventionalized visual systems (i.e., they consist of a more or less fixed number of visual features, such as axes, labels, and data points). Visually inspecting these spatial systems is crucial to successfully extracting information from a graph. In contrast to irrelevant data points, seductive details can be considered extraneous material that may interfere with the process of graph reading through distraction or disruption (see Section 2). In graphs, seductive material may not only be distracting in regard to its content but also in regard to spatial aspects (i.e., seductive details add irrelevant visual elements to an otherwise highly structured spatial system).

Secondly, we apply the principles of the seductive details effect from learning and retention to the area of graph reading tasks that require students' immediate performance. Nevertheless, mechanisms identified in the context of learning should be applicable to immediate performance at least to some extent because processing and understanding the material have similar fundamental requirements to those necessary for learning, namely, encoding the given information and constructing a coherent mental model in order to solve the task (see also Lindner, Ihme, Saß, & Köller, 2016). In their study on the effect of representational pictures, Lindner et al. (2016) showed that the multimedia effect on learning (see Mayer, 2009; Mayer & Fiore, 2014) also occurred during problem solving in a multiple-choice test and affected students' test performance. Seductive details may likewise affect the processing of graphs because the graph reading process relies heavily on the visual processing of different elements in the graph, making it vulnerable to the effects of distraction and disruption.

Previous studies of the seductive details effect typically employed a time constraint during the learning phase in order to limit the participants' cognitive resources (see Rey, 2012 for an overview). Although this approach may often be important for learning scenarios, it may not be necessary in the context of graph comprehension. Locating and comparing multiple data points is a complex task in itself that can put a high strain on working memory (e.g., Friel, Curcio & Bright, 2001; Kim & Lombardino, 2015). Rather than limiting cognitive resources by means of time constraints, we aimed to put a burden on the participants' working memory by choosing complex graph reading tasks that require performing multiple operations and considering multiple elements at the same time. In exchange, this approach allowed us to switch the traditional logic and introduce processing time as a dependent measure. Accordingly, we expected seductive details not only to make the graph reading process more difficult and error prone but also to result in longer processing times.

4 | USING EYE TRACKING TO GAIN INSIGHT INTO THE GRAPH READING PROCESS

Using eye tracking as means to gain insight into cognitive processes has a long tradition that revolves around an idea called the *eye-mind hypothesis* (Just & Carpenter, 1980; for introductions on the method of eye tracking, see,e.g., Duchowski, 2007; Holmqvist et al., 2011). Basically, the eye-mind hypothesis embraces the assumption that the location of eye-fixation also represents the focus of attention (i.e., it is assumed that we process the visual information we are currently looking at). Although researchers have discussed some shortcomings of the method (e.g., Hyönä, 2010; Wright & Ward, 2008), a great number of empirical studies have shown that eye-fixation measures and cognitive performance are closely related (e.g., Canham & Hegarty, 2010; Jarodzka, Scheiter, Gerjets, & van Gog, 2010; Lindner, Eitel, Strobel, & Köller, 2017). In contrast to other process tracing methods (e.g., verbal protocols; Ericsson & Simon, 1980; van Gog, Kester, Nievelstein, Giesbers, & Paas, 2009), remote eye tracking does not place additional load on participants' working memory and is unobtrusive for the participant (e.g., Hyönä, 2010).

Eye tracking is especially useful for the study of attentional processes that occur during processing of multimedia and learning materials because it provides detailed insight into the allocation of visual attention (Mayer, 2010; van Gog & Scheiter, 2010). In the context of graph reading, eye tracking allows allocating the processing time to the current spatiotemporal attention of the graph reader. In a number of recent eye tracking graph studies, researchers were able to successfully attribute processing time to important subregions of graph tasks (i.e., *x*-axis, *y*-axis, legend, pattern, question, and answers; Kim & Lombardino, 2015; Peebles & Cheng, 2003; Strobel et al., 2016). In the present study, eye tracking enables us to track how much time can be attributed to the processing of specific regions in the graph, such as seductive details or specific graph regions. Furthermore, eye-fixation patterns allow us to distinguish between potential explanations of the seductive details effect (cf. Harp & Mayer, 1998): If seductive details affect graph readers via distraction, this should be reflected in longer total processing times and additional fixations on the seductive details regions. However, if seductive details affect graph processing via disruption, readers need to revisit regions of the graph they inspected before the interruption occurred. Thus, longer fixation times on other graph regions (e.g., axes and labels) would be expected in addition to eye fixations on seductive details.

5 | RESEARCH HYPOTHESES

In this study, we examined the effects of two types of seductive details placed in regular bar graphs in the context of graph comprehension: seductive text and seductive illustrations. We also focused on the role of students' WMC in processing graph reading tasks with the different variations of seductive details compared with regular graph tasks. We applied eye tracking methodology to investigate two potential explanations for the seductive details effect: distraction and disruption. On the basis of the theoretical and empirical framework, we formulated the following hypotheses:

(1) Seductive details hypothesis: Seductive details (text or pictures) in graphs are expected to distract students' attention from the functional elements of the graph or disrupt the graph reading process. Accordingly, we expected that graph readers make more mistakes and take more time to complete a task when they interpret graphs with seductive details compared with conventional graphs.

(2) Potential causes of the seductive details effect:

   a. Distraction hypothesis: If the seductive material affects graph reading via distraction from the relevant information, students should require additional processing time as reflected in eye fixations on the seductive details. However, as processing time was not limited, we expected that fixation times on other regions would be unaffected by seductive details in a graph.

   b. Disruption hypothesis: If the seductive material affects graph reading via disruption, readers would need to start over where they left off before they were interrupted. Students should require additional processing time due to additional fixation times on the previously inspected regions. Thus, both additional fixation times on the seductive details regions and longer fixation times on other graph regions (e.g., axes and data points) are to be expected.

(3) Vulnerability hypothesis: When solving graph reading tasks, students need to hold multiple variables in working memory, making the process especially difficult for individuals with a low WMC. As the processing of seductive material may induce an additional burden on working memory, students with a lower WMC are expected to be more severely affected by seductive details than students with a higher WMC.

6 | METHOD

6.1 | Sample and study design

In our experiment, we examined a German sample of N = 68 university students from different faculties of one university in northern Germany (81% female, M_{age} = 22.81 years). We distributed our call for participants using multiple posters that were hung up at different university buildings to recruit participants across multiple faculties. All students had normal or corrected to normal vision. Originally, 73 students were approached, but data from five students (7%) were excluded from the analysis after visual inspection of scan paths because they revealed a poor eye tracking data quality (e.g., displaced scan paths and loss of tracking). The assessment comprised a set of graph task items as well as a paper–pencil questionnaire to assess demographic information. We employed a repeated-measures within-subject design in which we varied the presence of seductive details in the graph task items in three conditions: no seductive details versus seductive pictures versus seductive text. The students completed five items in each experimental condition, resulting in a total of 15 graph task trials.

We assessed total processing time (i.e., the time from task onset to task completion) and error rate as dependent variables while controlling for WMC. Additionally, we collected eye tracking data to determine the amount of time devoted to different functional areas of the task material. Finally, we adapted a short graph literacy scale to measure the students' level of experience in graph reading (see Strobel et al., 2016).

6.2 | Material and measures

6.2.1 | Graph task

For the computer-based graph task, we exclusively used bar graphs to avoid effects of the graph type on task performance (see,e.g., Peebles & Cheng, 2003; Strobel et al., 2016). Each of the 15 graph task items consisted of a lead-in statement, followed by a single bar graph, the question, and four multiple-choice answer options (see Figure 1). The position of the one correct answer was determined by a one-time randomization (i.e., one randomization that was used for all students).

To complete an item, students had to perform multiple comparisons among all six data points in the graph, find an optimal solution with regard to the question (i.e., a combination of data points that fit a given criterion), and select the correct answer among four options in a classical multiple-choice format (single choice). For example, one item asks the reader to identify the combination of food with the lowest overall amount of calories among four given combinations (see Figure 2 for a translated example item). In order to complete the item, participants had to extract the data for each combination, compute the sum of calories, keep the results in mind, and compare them among each other to find the optimal solution. In this task, working memory is not limited by time constraints, but instead, it is burdened by the number of operations that need be performed and the number of elements that need to be considered at the same time.

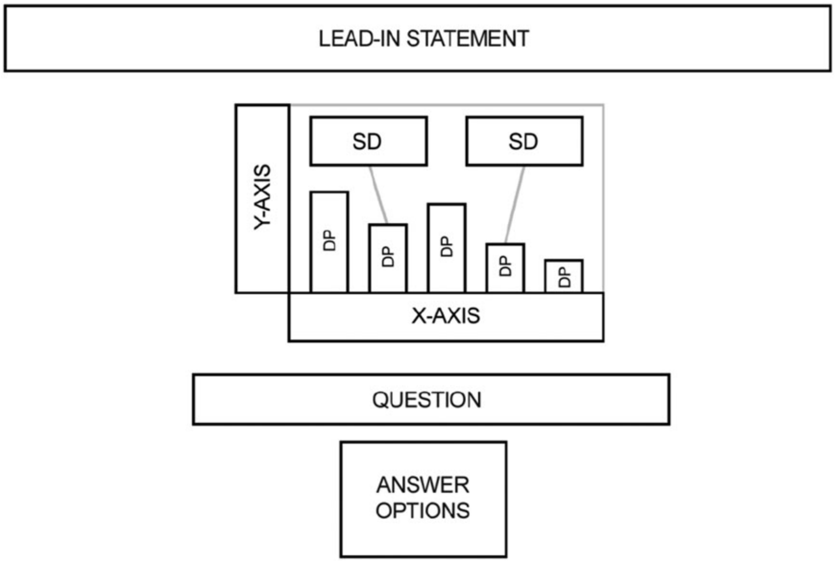

FIGURE 1 Schematic representation of the areas of interest defined for the eye tracking analysis in the experimental conditions. DP: data point; SD: seductive detail (either text or picture)

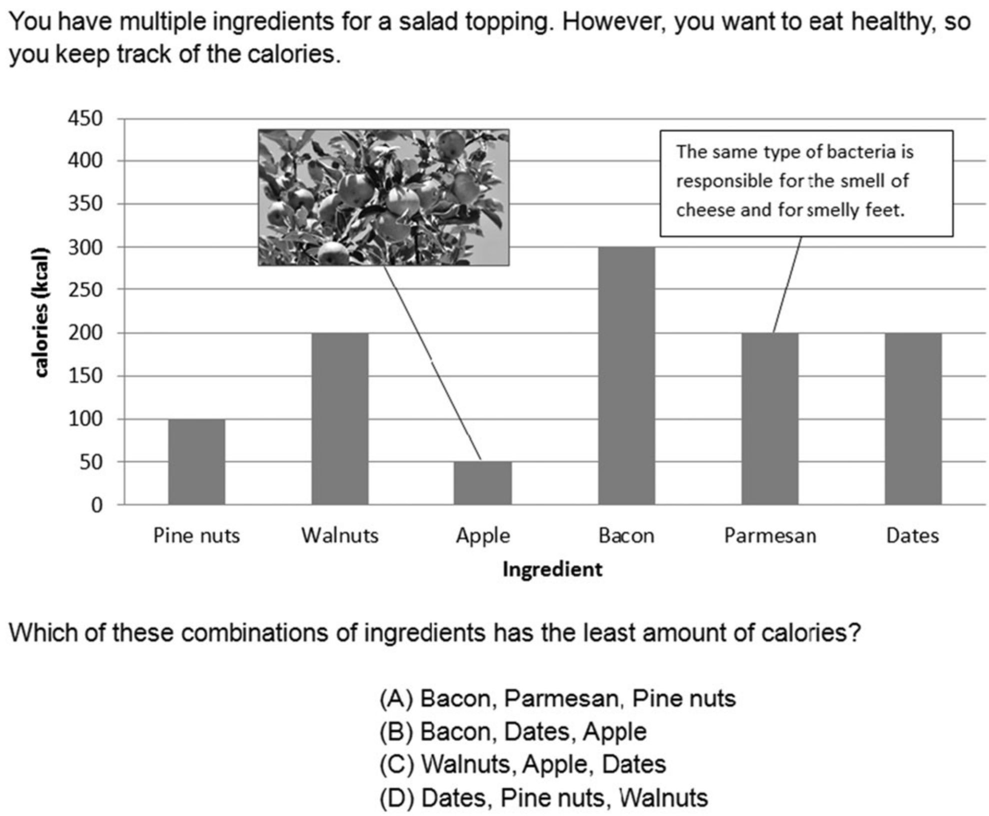

FIGURE 2 Translated example item of the graph task showing a picture from the seductive picture condition (left) and a text from the seductive text condition (right). In the actual experiment, items were displayed in color and showed two pictures, two short texts, or no seductive material at all

Regarding the item contents, we drew a sample from a variety of different topics (e.g., food and sports), but no specific prior knowledge was required to solve the tasks. The 15 different items were once divided into three groups of five items. For each participant, the item groups were randomly assigned to one condition (control, seductive text, and seductive pictures). Subsequently, the positions of all items were randomized. This approach ensured that the sequence of items, the sequence of conditions, and the starting condition were completely randomized. All bar graphs were constructed in the same manner: The bar graphs consisted of a categorical *x*-axis (e.g., food name) and a continuous *y*-axis that showed quantitative data (e.g., number of calories). All graphs showed six data points, each of which had to be considered in order to identify the correct answer. As experimental variations, we either included two pictures in the graph, visually illustrating two of the data points, or two short texts describing two of the data points (e.g., "If heated for a longer time period, raw eggs may explode in the microwave," illustrating a data point for "eggs"). Both the pictures and texts had a rectangular shape of similar size and were included in the pattern area of the graph, directly above the bars. Seductive details were carefully positioned so that they would not occlude any data points or functional parts of the graph. Identical labels were used in all conditions. Lead-in statements, item stem, and multiple-choice options did not differ between the experimental and control conditions.

6.2.2 | Working memory capacity

We adapted a computerized spatial working memory capacity (SWMC) task described in Oberauer, Süß, Schulze, Wilhelm, and Wittmann (2000). The task is constructed "as a spatial equivalent to reading span" (p. 1026). Items of the SWMC task consisted of a short instruction and a series of (either two or three) patterns, presented sequentially on the computer screen. The task consisted of two practice items, followed by eight items with two patterns each and six items with three patterns each. Patterns were drawn on the screen by partially filling the cells of a 3 × 3 matrix. Participants were instructed to mentally rotate the pattern either 90° to the right or 90° to the left and to remember the outcome. Each pattern was displayed for 3 s, followed by an inter stimulus interval of 200 ms. After a series of (either two or three) patterns, students had to fill a respective number of blank 3 × 3 matrices with the rotated patterns in the same order they were presented. One point was scored for every pattern that was remembered correctly. Oberauer et al. (2000) argued that "the main requirement of this task should be simultaneous storage and transformation, although retention of spatial patterns can be assumed also to require coordination of the single cells into an integrated structure" (p. 1026).

6.2.3 | Graph literacy

A short questionnaire was employed to assess the students' graph literacy using 5-point Likert-scaled items. The scale comprised four items (i.e., "I am familiar with bar graphs," "I have used bar graphs before," "I often use graphs," and "I feel confident in reading graphs."). The reliability of the graph literacy scale was satisfactory (Cronbach's α = 0.74).

6.3 | Apparatus

Items of the graph task were presented on a 19-inch screen with a 1280 × 1024 pixel resolution, using the software Experiment Center 3.5 from SensoMotoric Instruments (SMI, Teltow, Germany). Each item appeared on a single screen. Students were seated in front of the computer screen at a distance of approximately 70 cm. The font size of the text was about 2 cm (approximately 1.6° visual angle). The students' eye movements were recorded using a video-based remote eye tracking system (SMI iView X™RED-m; 120 Hz sampling rate) and the corresponding SMI software iView X™. The system was calibrated for each session using an animated 8-point calibration image and subsequent validation. The calibration accuracy was below 0.5° visual angle for all students on both the x and y coordinates (range: 0.04 to 0.49; M_x = 0.29, SD_x = 0.09; M_y = 0.30, SD_y = 0.10).

6.4 | Procedure

Students were tested in single sessions. Prior to the experiment, they were familiarized with the procedure and the eye tracking system. Subsequently, the students completed the graph task items on a computer, while their eye movements were recorded. We did not impose a time limit for item completion in order to better resemble a real-life situation. However, we recorded the students total processing time, which is defined as the time a specific participant needed to complete a specific trial of the graph task. The paper–pencil questionnaire for assessment of demographic information was administered after completion of the graph task. The complete assessment cycle took about 45 min. Students later received 10 euros for their voluntary participation in the study.

6.5 | Analysis

6.5.1 | Eye-movement data pre-processing

We analyzed the eye-movement recordings using a dispersion-based algorithm implemented in the Begaze™ software, version 3.5, from SMI. A fixation was detected when an eye movement lasted for at least 80 ms on a position with a maximum dispersion of 100 pixels. In addition, we conducted a careful visual inspection of all students' scan paths in every task to ensure the quality of the eye-movement data. Poor tracking quality led to an exclusion of the respective participant.

We used total fixation time on predefined areas of interest (AOI) as the eye-movement measure for our analyses. Total fixation times indicate how much time a participant spent fixating the predefined AOIs during a trial (i.e., the total time devoted to a specific area; Holmqvist et al., 2011). For educational tasks using the multiple-choice item format, total fixation times provide a valid indirect measure of attention distribution and cognitive processing (e.g., Lindner et al., 2014).

In the tradition of recent graph studies (e.g., Kim & Lombardino, 2015; Peebles & Cheng, 2003; Strobel et al., 2016), we divided the graph regions into multiple rectangular AOIs. The x-axis and y-axis, including the respective labels, were grouped together as *axes and labels*. Each bar in the graph was also covered by its own AOI, and all six bars were grouped together as *data*. Another six AOIs for the lead-in statement, the question, and the four multiple-choice answer options were grouped together as *item stem and options*. All reported data refer to these AOI groups. For a visualization of the AOI configuration, see Figure 1.

6.5.2 | Linear mixed-effects models

Data were analyzed using R, version 3.4.3 for Windows (R Core Team, 2017). Repeated measures were nested both within students and items, with each measure belonging uniquely to one students and one item. This data structure can be described as clustered or hierarchical with cross-classified effects for students and items (Snijders & Bosker, 2012). Regular analysis of variance models can yield inflated type I error rates when the data are clustered in this manner (Dorman, 2008), so we applied *linear mixed-effects models* (LMMs) to account for the clustered structure of the data (for introductions, see Snijders & Bosker, 2012; Quené & van den Bergh, 2008). This type of model can be understood “as a series of interrelated regression models that explain sources of variance at multiple levels of analysis, such as at the experimental stimuli and person levels” (Hoffman & Rovine, 2007, p. 102). LMMs can model fixed effects and random effects simultaneously: Fixed effects on the one hand aim to identify typical rates of change in the criterion variable that can be attributed to aspects of the experimental design (e.g., the manipulation). Random effects on the other hand aim to identify unsystematic rates of change (e.g., due to differences between items and students, respectively).

We used the R package lme4 (Bates, Maechler, Bolker, & Walker, 2015) to perform (generalized) linear mixed-effects analyses of the relationships between the experimental conditions and several outcome variables: error rate, total processing time, total fixation time on item stem and options, total fixation time on axes and labels, total fixation time on data, and total fixation time on seductive details in the graph. The LMMs include random intercepts for both students and stimuli. Models were fitted by the restricted maximum likelihood criterion, because it yields better type I error rates for smaller groups when testing fixed effects than estimates with the maximum likelihood criterion (Manor & Zucker, 2004; Snijders & Bosker, 2012). The control condition was chosen as the reference group in all LMMs. To calculate differences between the two experimental conditions (i.e., seductive text and seductive pictures) in the form of post hoc contrasts, we made use of the “delta method” implemented in the R package car (Fox & Weisberg, 2011). Degrees of freedom for statistical tests of fixed effects in the LMMs were determined in accordance with the rule described in Snijders and Bosker (2012), that is, as $df = N - q - 1$, where N is the minimum number of upper-level units in the sample (here: $N = 15$ stimuli) and q is the number of explanatory variables included in the model.

6.5.3 | Model comparisons

For all our dependent variables, the model comparisons followed the same structure: Starting with an empty model including random intercepts for students and stimuli (Model 0 [M0]), we first added SWMC as a covariate (Model 1 [M1]), followed by a model that included the fixed effects for experimental conditions regarding the seductive details integration (Model 2 [M2]), and finally, we considered potential interaction effects of seductive details and SWMC (Model 3 [M3]). For the first two dependent variables (error rate and total processing time), we report the full models with all coefficients in Tables 1 and 2. For the remaining models that address the eye-movement patterns, we only report model comparison parameters to facilitate inspection and save space (see Table 3).

We computed likelihood-ratio tests and multiple R^2 measures for the LMMs to assert if the inclusion of predictor variables constitutes a significant addition to the model. For the LMMs, we computed the two R^2 measures suggested by Snijders and Bosker (2012) and Nakagawa and Schielzeth (2013). For the generalized linear mixed-effects models (GLMMs), we calculated the corresponding R^2 measure by Nakagawa and Schielzeth and the pseudo R^2 measure suggested by Nagelkerke (1991).

In addition to the more traditional indicators, we computed Bayes factors to aid with the comparisons of our LMMs using the R package

TABLE 1 Comparison of fixed effects and random effects in the generalized linear mixed-effects models for error rate

	Model 0			Model 1			Model 2			Model 3		
Fixed effect	**Estimate**	***SE***	***z* value**	**Estimate**	***SE***	***z* value**	**Estimate**	***SE***	***z* value**	**Estimate**	***SE***	***z* value**
Intercept	−1.36***	0.19	−7.05	−1.36***	0.19	−7.20	−1.47***	0.22	−6.60	−1.46***	0.22	−6.56
SWMC				−0.30*	0.13	−2.38	−0.30*	0.13	−2.37	−0.19	0.17	−1.08
Pictures							0.12	0.20	0.63	0.10	0.20	0.53
Text							0.20	0.20	1.03	0.20	0.20	0.97
SWMC × Pictures										−0.03	0.03	−1.06
SWMC × Facts										−0.02	0.03	−0.67
Random effect	**Variance component**			**Variance component**			**Variance component**			**Variance component**		
Student	0.74			0.63			0.63			0.63		
Stimulus	0.28			0.27			0.27			0.28		
Residual	—			—			—			—		
R^2_{NK}	0.00			0.01			0.01			0.01		
R^2_{NS}	0.00			0.02			0.02			0.02		
LR test[a]				$\chi^2(1) = 5.39$*			$\chi^2(2) = 1.03$			$\chi^2(2) = 1.12$		

Note. LR: likelihood ratio; R^2_{NK}: R^2 measure suggested by Nagelkerke (1991); R^2_{NS}: R^2 measure suggested by Nakagawa and Schielzeth (2013); SWMC: spatial working memory capacity (scaled).

[a]In comparison with the previous model.

*$p < 0.05$. ***$p < 0.001$.

TABLE 2 Comparison of fixed effects and random effects in the linear mixed-effects models for total processing time

	Model 0			Model 1			Model 2			Model 3		
Fixed effect	**Estimate**	***SE***	***t* value**	**Estimate**	***SE***	***t* value**	**Estimate**	***SE***	***t* value**	**Estimate**	***SE***	***t* value**
Intercept	66.60***	3.14	21.22	66.60***	3.08	21.62	64.21***	3.20	20.04	64.28***	3.20	20.09
SWMC				5.44*	2.42	2.24	5.48*	2.32	2.25	3.83	2.59	1.48
Pictures							3.28*	1.45	2.26	3.21*	1.45	2.21
Text							3.85*	1.45	2.66	3.82*	1.45	2.64
SWMC × Pictures										0.21	0.23	0.91
SWMC × Facts										0.57*	0.24	2.41
Random effect	**Variance component**			**Variance component**			**Variance component**			**Variance component**		
Student	395.40			371.40			372.80			375.64		
Stimulus	54.01			54.01			54.66			53.58		
Residual	342.01			342.01			339.56			338.02		
R^2_{SB}	0.00			0.03			0.03			0.03		
R^2_{NS}	0.00			0.04			0.04			0.04		
LR test[a]				$\chi^2(1) = 4.96$*			$\chi^2(2) = 8.14$*			$\chi^2(2) = 5.94$		
Bayes factor[a]				2.19			0.59			**0.19**		

Note. Bayes factors >3 and <0.33 are printed in bold type. LR: likelihood ratio; R^2_{SB}: R^2 measure suggested by Snijders and Bosker (2012); R^2_{NS}: R^2 measure suggested by Nakagawa and Schielzeth (2013); SWMC: spatial working memory capacity (scaled).

[a]In comparison with the previous model.

**p* < 0.05. ***p* < 0.01. ****p* < 0.001.

BayesFactor (Morey & Rouder, 2015).[1] Bayes factors allow for a simplified Bayesian approach to model comparisons by evaluating the posterior odds in favor of and against the models included in the comparison (Raftery, 1995). In the context of this study, Bayes factors were deemed useful because they provide a continuous measure of "evidence" in favor and against the null and alternative hypotheses on an intuitive scale (Kass & Raftery, 1995; Raftery, 1995). As a rough guide, it has been suggested that Bayes factors >3 may be interpreted as support in favor of the more general of the two models (i.e., the alternative model), whereas Bayes factors >0.33 indicate support in favor of the more restrictive model (i.e., the null model). For a more detailed introduction to the theory and interpretation of Bayes factors, see Kass and Raftery (1995).

7 | RESULTS

\Along with other biographic information, students were asked to rate their graph literacy on a scale that comprised four items, each of which used a 5-point rating scale. The mean rating of graph literacy in the current sample was $M = 3.39$ ($SD = 0.81$, range = 1.25 to 5) with a negative skewness (−0.38) indicating that the mass of the data was distributed with a concentration on the upper half of the scale.

[1]Please note that the BayesFactor package (Morey & Rouder, 2015) currently only supports the calculation of Bayes factors for models with continuous but not categorical outcome variables (e.g., the GLMMs for error rate). For this reason, we report Bayes factors for all models except the GLMMs for the error rate.

7.1 | Error rate

The mean error rate in the graph task, across participants, was about 22% in the control setting, 25% when seductive pictures were present, and 26% when seductive text was present. We used a series of GLMMs to estimate the relationship between the students' error rate and the experimental conditions while controlling for working memory (Table 1). First, we computed an empty model with random intercepts for students and stimuli (M0). The estimates of the GLMMs are given in log odds (i.e., the logarithm of the odds, $p/(1-p)$, where p represents a given probability). Translated into a frequency, the estimated error rate across all conditions was about 20% (i.e., 80% correct answers). The main effect of SWMC was significant according to the likelihood-ratio test (M1; $\chi^2 = 5.39$, $df = 1$, $p = 0.020$). As indicated by the model parameters, an increase of one standard deviation in SWMC resulted in an estimated decrease in error rate by approximately 4 percentage points (i.e., an error rate of 16%). The subsequent addition of the experimental conditions did not yield significant changes in the likelihood ratio, neither for main effects (M2) nor for the interaction effects (M3). Differences in the R^2 measures between these models were barely noticeable as well (<0.01).

We hypothesized that the error rate would be higher in the seductive details conditions (i.e., when a picture or a fact is included in the graph) compared with the control setting with no additional content and that students with a low WMC would be more vulnerable to the seductive details effect. Contrary to our expectations, error rates did not differ significantly between experimental and control conditions, and SWMC did not affect the absence of the seductive details effect.

TABLE 3 Model comparisons of the linear mixed-effects models for total fixation times on the four AOI groups

	Model 0 (M0)	Model 1 (M1)	Model 2 (M2)	Model 3 (M3)
Item stem and options				
R^2_{SB}	0.00	0.02	0.02	0.02
R^2_{NS}	0.00	0.03	0.03	0.03
LR test[a]		$\chi^2(1) = 3.71$	$\chi^2(2) = 1.14$	$\chi^2(2) = 4.43$
Bayes factor[a]		1.22	**0.02**	**0.10**
Axes and labels				
R^2_{SB}	0.00	0.02	0.02	0.02
R^2_{NS}	0.00	0.03	0.03	0.03
LR test[a]		$\chi^2(1) = 3.89^*$	$\chi^2(2) = 7.01^*$	$\chi^2(2) = 5.75$
Bayes factor[a]		1.27	0.36	**0.19**
Data				
R^2_{SB}	0.00	0.01	0.01	0.01
R^2_{NS}	0.00	0.01	0.02	0.02
LR test[a]		$\chi^2(1) = 2.47$	$\chi^2(2) = 5.93$	$\chi^2(2) = 3.97$
Bayes factor[a]		0.63	**0.21**	**0.09**
Seductive details				
R^2_{SB}	0.00	0.00	0.28	0.28
R^2_{NS}	0.00	0.00	0.28	0.28
LR test[a]		$\chi^2(1) = 0.03$	$\chi^2(2) = 353.77^{***}$	$\chi^2(2) = 0.25$
Bayes factor[a]		**0.10**	**>100**	**0.02**
White space[b]				
R^2_{SB}	0.00	0.00	0.00	0.00
R^2_{NS}	0.00	0.00	0.01	0.01
LR test[a]		$\chi^2(1) = 0.53$	$\chi^2(2) = 0.09$	$\chi^2(2) = 0.45$
Bayes factor[a]		**0.17**	**0.12**	**0.03**

Note. Bayes factors >3 and <0.33 are printed in bold type. AOI: areas of interest; LR: likelihood ratio; M0: empty model with random intercepts for students und stimuli. M1: including main effects of spatial working memory capacity. M2: including main effects of condition. M3: including interaction effects of spatial working memory capacity and conditions; R^2_{NS}: R^2 measure suggested by Nakagawa and Schielzeth (2013); R^2_{SB}: R^2 measure suggested by Snijders and Bosker (2012).

[a]Comparison with the previous model.

[b]Total fixation time outside of defined AOIs.

$^*p < 0.05$. $^{***}p < 0.001$.

7.2 | Processing time

A series of LMMs was used to estimate the relationship between the students' processing time and the experimental conditions as well as WMC (Table 2). We computed an empty model again with random intercepts for students and stimuli (M0). The estimates are given in seconds. The inclusion of SWMC was a significant improvement of the model (M1; $\chi^2 = 4.96$, $df = 1$, $p = 0.026$) as was the subsequent inclusion of condition main effects (M2; $\chi^2 = 8.14$, $df = 2$, $p = 0.017$). Again, differences in the R^2 measures were relatively small. Also, the inclusion of interaction effects did not improve the model significantly (M3; $\chi^2 = 5.94$, $df = 2$, $p = 0.051$).

We hypothesized that the processing time would be higher in the seductive details conditions compared with the control condition. Examining M2, the estimated processing time in the control condition was, on average, about 64.2 s. In this model, processing time was significantly longer by about 3.9 s in the seductive text condition ($p = 0.007$) and by about 3.3 s in the seductive pictures condition ($p = 0.002$). In addition, the assessment of post hoc contrasts revealed that the conditions for seductive text and seductive pictures did not differ significantly from one another (Estimate = 0.58, SE = 1.44, $t = 0.40$, $p = 0.699$). These findings are in line with the seductive details hypothesis. We examined M3 with regard to the vulnerability hypothesis. Model comparison parameters unanimously suggest that the inclusion of interaction effects did not improve the model, indicating that SWMC did not affect the extent of the seductive details effect.

7.3 | AOI analysis[2]

Figure 3 shows a stacked bar chart of the average total fixation times, grouped by experimental condition and with blocks pertaining to the four AOI groups (item stem and options, axes and labels, data, seductive details, and white space). Differences in fixation times on the AOI groups can help us distinguish between effects of distraction and

[2]We further analyzed the number of re-fixations on the AOI groups. Because the results for re-fixations did not lead to different statistical conclusions compared with those reported for total fixation time, we do not report re-fixation parameters in favor of the conciseness of the article.

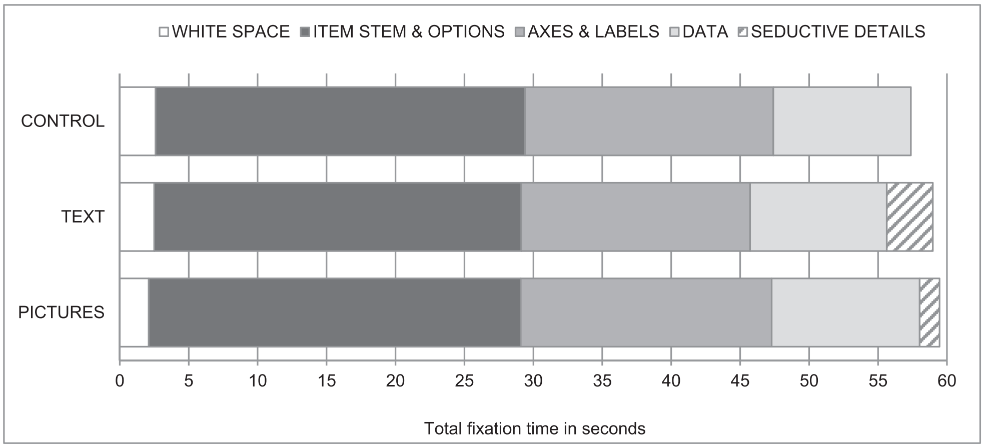

FIGURE 3 Average total fixation times on the four areas of interest (AOI) groups across all participants, grouped by experimental condition (control, seductive text, and seductive pictures) and with blocks pertaining to AOI groups. White space: space outside of the AOIs

disruption. We hypothesized that additional fixation times on the seductive details regions but not on other regions would support the distraction hypothesis, because this pattern would indicate that students attended to the seductive details, but the graph reading process was otherwise unaffected. In contrast, additional fixation times on both seductive details and the other regions would be in favor of the disruption hypothesis. This pattern would suggest that students needed to revisit previously inspected regions of the graph after the reading process was disrupted. Results of the model comparisons are provided in Table 3 (to facilitate inspection and save space, we only report model comparison parameters).

In the control condition, the average total fixation time on item stem and options was approximately 27 s, which was also the longest fixation time compared with the other AOI groups. The average total fixation time on axes and labels was approximately 18 s and 10 s on the data points (bars). Compared with the other conditions, there were virtually no differences in total fixation times between the experimental conditions except for a slight decrease in the time on the axes and labels region in the text condition by about 1 s. Additional fixation times on the seductive details regions were approximately 3 s in the text condition and 1.5 s in the pictures condition.

For each of the AOI groups, we computed a series of LMMs for the relationship between total fixation times and the experimental conditions using the same procedures we employed for error rate and processing time. As the descriptive data already suggested, there were little to no differences in the total fixation times between the experimental and control conditions.

Regarding the total fixation time on item stem and answer options, neither the inclusion of main effects nor the addition of interaction effects yielded a significant change in the likelihood ratio, which is mirrored by only small changes in the R^2 measures. The Bayes factors for M2 and M3 likewise indicated that the experimental conditions did not affect the total fixation times on the AOI regions for item stem and answer options. Model comparisons for total fixation times on axes and labels as well as the fixation times on data regions paint a similar picture with virtually no differences between experimental and control conditions as indicated by the negligible differences between models in terms of R^2 and Bayes factors consistently below 0.33.

The analysis of total fixation times on the seductive details regions is a notable exception to this pattern. However, this was to be expected because there were, by design, no seductive details present in the control condition. All indicators show evidence for main effects of condition on the total fixation time on the seductive details regions (M2). On average, the estimated total fixation time on seductive details in the pictures conditions was approximately 1.4 s (SE = 0.12, t = 8.73, p < 0.001) and approximately 3.4 s in the text condition (SE = 0.16, t = 20.76, p < 0.001). However, the addition of interaction effects with SWMC (M3) did not significantly improve the model. This finding indicates that students with different levels of SWMC were not reacting differently to the presence of seductive details.

8 | DISCUSSION

In this study, we examined the seductive details effect in the context of graph comprehension while accounting for individual differences in SWMC. In addition, we employed eye tracking methodology to gain insight into the process of graph reading and how it is affected by our experimental manipulation of the graph tasks with either seductive text or seductive pictures.

Students completed multiple computerized graph reading items in a within-subject repeated-measures design. The items either included thematically related but task-irrelevant pictures, texts, or no seductive details at all. Measures of error rate and processing time were examined to determine the extent of the seductive details effect in the context of graph comprehension. However, performance in the graph reading task was essentially unaffected by the inclusion of seductive details in the graph task items. As indicated by the fixation times on AOIs, the graph comprehension process did not differ in the experimental conditions with one notable exception: Students exhibited additional processing time that can be attributed to fixations on the seductive details regions. Higher levels of WMC on the other hand did significantly lower the error rates, but SWMC did not moderate the presence, absence, or size of the seductive details effect. In the following section, we will discuss the seductive details effect, the role of WMC, and the scope of this study separately and in greater detail.

8.1 | The seductive details effect in the context of graph comprehension

Results indicate that seductive details did not unfold all of their anticipated detrimental effects (cf. Harp & Mayer, 1997; Lehman et al., 2007; Rowland-Bryant et al., 2009) in the context of graph comprehension. We hypothesized that the processing of graph reading tasks would take longer and would be more error prone. By analyzing multiple GLMMs, we found that the error rate was unaffected by the inclusion of seductive details, whereas processing times were elevated by about 3 s in the seductive pictures condition and about 4 s in the seductive text condition. Model comparisons for the seductive details effect on eye-fixation times (see Table 3) revealed that processing of the graph task items was mostly unaffected by the experimental conditions, which was also evident by examining the descriptive statistics of total fixation times (see Figure 3). The only noticeable exception to this pattern was a few additional seconds of fixation time on the seductive details regions. This finding suggests that students (shortly) directed their attention to the seductive details, adding a few seconds of additional time needed to complete the task. Otherwise, task processing was mostly unaffected by the presence of seductive details.

We hypothesized that seductive details might be distracting and/or disruptive because diagrams are highly conventionalized graphical systems and thus might be vulnerable to the inclusion of external elements that are not part of the convention. Contrary to our expectations, students had no difficulty solving the graph task items even when seductive details were present. In comparison, as another example, the addition of task-irrelevant data points in graphs can noticeably impair the graph reading process (Strobel, Lindner, Saß, & Köller, in press). This is probably because they are an integral part of the graph and initially indistinguishable from the important information. However, a recent study on seductive details suggests that readers pay less attention to seductive material when they are made aware that the details only show task-irrelevant information (Peshkam, Mensink, Putnam, & Rapp, 2011). Moreover, Eitel, Bender, and Renkl (this issue) were able to show that the seductive details effect completely disappeared when participants were made aware which information was irrelevant, showing no detrimental effects on learning outcomes. Accordingly, a possible explanation for our findings might be that students were immediately able to tell that the seductive material was irrelevant to the task. This idea is supported by two notions: First, we placed the seductive material in such a way that it did not occlude elements or paths that are essential to the graph reading process. Thus, it was possible to largely ignore the seductive material, given a person was fully aware of the task and the conventions of the graphical system. Second, ratings of graph literacy concentrated on the upper half of the scale, indicating that the participants were familiar with the bar graph format that we used in this study. Taken together, the highly conventionalized nature of graphs (in conjunction with high graph literacy) may have had a shielding effect against negative influences of external elements such as seductive details. Thus, they may not pose a big threat for the graph comprehension process for individuals who are familiar with graphs.

8.2 | Distraction and disruption

In the seductive details literature, multiple causes of the seductive details effect are discussed (see,e.g., Harp & Mayer, 1998; Sanchez & Wiley, 2006). We identified distraction and disruption as the most likely causes of the seductive details effect in the context of graph comprehension. Distraction happens when a reader's attention is seduced away from the relevant information and towards the more interesting but irrelevant material. Disruption describes the hypothesis that the detrimental effects of seductive details are the result of an interruption of the mental model construction process during comprehension.

In our study, eye-movement data were used to help us identify possible causes of effects induced by seductive details in the context of graph comprehension. If seductive details affect readers through distraction alone, additional eye fixations would occur on the seductive details regions but not on other regions. Instead, if the graph reading process is affected by disruption, additional eye fixations would occur on other graph regions as well, because readers would need to start over where they left off (Sanchez & Wiley, 2006).

Although seductive details showed only small effects on the graph comprehension process in general, there is tentative evidence for the distraction hypothesis over the disruption hypothesis. Our analyses of total fixation times on different graph regions revealed that additional processing time can be almost completely attributed to additional fixation time on the seductive details regions in the two experimental conditions. Model comparisons for the remaining AOI groups unanimously suggest that there were no substantial differences in the fixation times on these regions. Although we found a short distraction in the range of a few seconds on average, there was no evidence for disruption as the fixation times on other regions were largely unaffected by both the experimental conditions, seductive text, and seductive pictures.

8.3 | The role of SWMC

SWMC was related to both error rate and total processing time. A high SWMC was associated with a smaller error rate, indicating that SWMC aids graph reading performance. Furthermore, a high SWMC was associated with longer processing time as well. These findings suggest that a higher level of SWMC enabled readers to inspect the graphs more thoroughly and make fewer mistakes.

In addition, our results indicated that SWMC did not affect the absence, presence, or size of the seductive details effect. This was true for both error rates and total processing time as well as for the fixation times on different regions of the graph. Although Sanchez and Wiley (2006) found that individuals with a low WMC were especially vulnerable to the seductive details effect in the context of text comprehension, we did not find the same effect on the performance in the graph reading task. However, it is important to note that there were no main effects of seductive material on error rates in the first place. If future research is able to identify conditions under which seductive details in graphs affect performance in graph reading tasks, the role of working memory should be evaluated in greater detail once again.

8.4 | Limitations and future research

Although traditional research on the seductive details effect was focused on text comprehension on the one hand and effects on retention on the other hand (e.g., Lehman et al., 2007; Mayer et al., 2008; Rey, 2011; Rowland-Bryant et al., 2009), we evaluated the effects of seductive details on immediate performance in the context of graph comprehension. It can be argued that understanding and processing share the same fundamental requirements with learning and retention (i.e., encoding information and constructing a coherent mental model; Lindner et al., 2017), but they are not one and the same. For example, retention also requires the storage of information in long-term memory and the ability to access it at a later point. Future studies of the seductive details effect in graphs could evaluate measures of retention alongside performance indicators. Furthermore, we placed seductive material directly in the graphs. Future studies could evaluate the effects of seductive details on graph comprehension in more traditional compositions (i.e., as part of the accompanying text) to paint a more comprehensive picture.

It is important to note that the present study embraces a specific graph reading task (comparison of multiple data points) and only one graph type (bar graphs). Although point comparison is a typical task, graph reading also comprises a number of equally common tasks, such as point location and identification of trends in the data (see,e.g., Bertin, 1983; Schnotz, 1994; Wainer, 1992), and other well-established graph types, such as line graphs and pie charts (see,e.g., Kosslyn, 1989; Lohse, Biolsi, Walker, & Rueter, 1994). It cannot be ruled out that seductive details affect other tasks and graph types differently.

In this study, we did not impose a strict time limit for the completion of the graph reading items. Although this is a common practice in the research on seductive details (e.g., Doolittle & Altstaedter, 2009; Towler, 2009) to further limit cognitive capacities, we were taking a different approach. Solving items of the graph reading task required that participants keep multiple data points in mind and compare them at the same time, thus imposing a burden on working memory. However, future studies could test the assumption that seductive details unfold stronger effects on graph reading when the time is limited as well.

Finally, the ratings of graph literacy in our sample were concentrated on the upper half of the scale, while error rates in the graph task were small at the same time. Behind this background of our sample and the results of the study, we would argue that seductive details in graphs can be easily identified by educated graph readers because graphs feature highly conventionalized compositions (i.e., axes, labels, and data points) that are easily distinguishable from external elements such as seductive text and seductive pictures. Learners of different ages and different levels of graph literacy should, thus, be compared in order to identify groups that may be more vulnerable to the effect of seductive details in graphs. This is underlined by the fact that the linear mixed-effects analyses revealed large variance components for students, highlighting the importance of individual factors for the graph comprehension process.

9 | CONCLUSION

Expanding both the research on seductive details and on graph comprehension, this study evaluated the effect of seductive details on the performance in graph reading tasks. Results indicate that neither seductive text nor seductive pictures affected the students' performance. However, seductive details elevated the processing time of the graph reading task. Analyses of eye-fixation parameters further revealed that a large portion of additional processing time could be allocated to the processing of seductive details but not to other regions of the display. This pattern of fixation times aligns well with one of the two mechanisms that were considered in this study: distraction rather than disruption. Because graphs are highly conventionalized systems, seductive details may likely be identified as task irrelevant by educated readers, preventing them from being disrupted after a brief distraction.

Seductive details did not seem to do their damage when placed in graphs. Although SWMC did not affect the seductive details effect, it was positively related to performance in the graph task. We suggest that future research should focus on the study of less experienced graph readers and individual factors in general.

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