It is not only about the depth of processing : what if eye am not interested in the text?

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It is not only about the depth of processing: What if *eye* am not interested in the text?

Abstract

This study aims at extending current research on how the interaction between cognitive processing and topic interest shapes the online learning process of students when learning from expository texts. We used eye tracking to monitor the reading and learning behaviour of 31 students in higher education. In addition, we used self-report questionnaires to map students' general disposition towards deep and surface processing and their topic interest. Cued retrospective think-alouds were conducted to capture students' levels of processing during learning from text. We examined the interaction between levels of processing and topic interest on eye movement measures. Results indicate that high-interested students who use more deep processing reread key sentences longer than detailed sentences and thus process these sentences more deeply. This study advances present knowledge in the field by focusing on the online learning process and stresses the importance of giving students learning contents that spark their interest.

Keywords

Processing strategies; Expository text; Eye tracking; Topic interest; Cued retrospective think-aloud

1. Introduction

Expository texts are an important medium through which higher education students acquire knowledge and understanding (Ariasi, Hyönä, Kaakinen, & Mason, 2017; Fox, 2009; Gillam, Fargo, & Roberston, 2009). Expository texts are used to explain or describe the learning content to the readers. The goal of an expository text is to present the reader with information so that the reader may learn something. This is in sharp contrast to story-telling or narrative texts that are meant to entertain the reader (Fox, 2009). Learning from an expository text is one of the most essential skills in higher education (Ariasi et al., 2017; Kirby, Cain, & White, 2012; McNamara, 2012; O'Brien, Cook, & Lorch, 2015). Therefore, considerable efforts have been made in educational research to better understand the learning process associated with learning from an expository text (Fox, 2009; Pressley & Afflerbach, 1995). During reading, students interact with the text, actually constructing their own mental representation of the text (Kendeou & O'Brien, 2018; Kintsch, 1998). How this mental representation is constructed depends on important cognitive and motivational characteristics that affect the quality of reading and learning (Alexander & Jetton, 1996; Fox, 2009; Kendeou & Trevors, 2012). However, empirical research that examines both cognitive and motivational characteristics during the learning process of text learning remains scarce (Alexander, 2017, 2018). The interplay between important motivational and cognitive characteristics during learning refers to the multidimensional nature of learning. Alexander (2017, 2018) argues that in order to fully understand the learning process, research should tap more explicitely into this multidimensional nature of learning.

An important cognitive characteristic that affects the quality of text learning is students' levels of processing (Alexander & Jetton, 1996; Fox, 2009; Kendeou & Trevors, 2012). Levels of processing refer to cognitive activities that students engage in when studying, and these processing activities are important for the development of knowledge and understanding (Vermunt & Donche, 2017; Vermunt & Vermetten, 2004). Although the relation between students' levels of processing and text learning has been examined during the online learning process with think-aloud protocols (Dinsmore & Alexander, 2016; Merchie & Van Keer, 2014a; Pressley & Afflerbach, 1995) and eye tracking (Catrysse et al., 2018; Catrysse et al., 2016), there is an even vaster amount of research that examined students' general disposition towards deep and surface levels of processing within one course context or throughout multiple course contexts or time (Fryer, 2017; Vermunt & Donche, 2017). Students' general disposition towards deep and surface processing can also have an important influence on how they learn from texts (Kirby et al., 2012), especially on what they perceive to be relevant or important in the text (Kendeou & Trevors, 2012). Previous research showed that a student's general disposition towards levels of processing influences how they process learning contents to some extent (Baeten et al., 2010; Catrysse et al., 2018; Kirby et al., 2012), especially if the learning task is related to what they usually need to study (Richardson, 2015).

An important motivational characteristic for text learning is topic interest (Alexander & Jetton, 1996; Krapp, 1999; Renninger & Hidi, 2011, 2016). It is assumed that topic interest is an important precondition for deeper cognitive processing (Alexander, 1997, 2017; Pintrich, 2004; Vermunt & Donche, 2017). Alexander (2017) even claims that whether students process the learning content deeply is reflective of the interest they bring to the text. Empirical research already showed that topic interest is related to deep-level learning outcomes, such as deep comprehension, recall of main ideas, elaborations and coherence of recall of main ideas (Krapp, 1999; Schiefele, 1999; Schiefele & Krapp, 1996). However, previous research has often neglected the multidimensional nature and the interplay between cognitive processing and interest when investigating the learning process when learning from expository text. Although the offline product of reading is influenced by the online learning process (Kendeou & Trevors, 2012; Kintsch, 1998), much of the learning takes place during reading and thus it is important to gain in-depth insight into the learners' online process of learning (Kendeou & Trevors, 2012). This study aims at extending current research on how the interaction between cognitive processing and interest shapes the online learning process of students when learning from expository texts. Before focusing on the present study, the relation between student characteristics and text learning, as well as measures that tap into the online learning process, are discussed below.

1.1. Student characteristics and text learning

Cognitive and motivational characteristics shape how students build a mental representation during text learning (Fox, 2009; Jarodzka & Brand-Gruwel, 2017; Kendeou & Trevors, 2012). With regard to cognitive processing, a main distinction has been made between deep and surface levels of processing (Vermunt & Donche, 2017). These different levels of processing are distinguished in important models of reading and learning, such as the Model of Domain Learning (Alexander, 1997), the Construction-Integration Model of comprehension (Kintsch, 1998), and models related to Students' Approaches to Learning (Richardson, 2015), such as the Learning Pattern Model (Vermunt & Donche, 2017). In the Learning Pattern Model, students with a general disposition towards deep levels of processing are described as having the intention to understand and to engage in meaningful learning. Students' with a general disposition towards surface levels of processing selectively memorize the learning content (Vermunt & Donche, 2017). Previous research on levels of processing during learning from text showed that deep processing activities include critiquing the reading, linking the text to prior knowledge, paraphrasing parts of the text, interpreting information in the text, linking the text to personal experiences, focusing on main themes and elaborating. Surface processing activities refer to rereading parts of the text, literally retelling, focusing on details and rehearsing (Dinsmore & Alexander, 2016; Fox, 2009; Pressley & Afflerbach, 1995; Schellings, van Hout-Wolters, Veenman, & Meijer, 2012). This research takes into account insights from the Model of Domain Learning (Alexander, 1997) and the Learning Pattern Model (Vermunt & Donche, 2017) and is thus situated at the crossroads of these models. As described by Alexander (2018) combining insights from several theories results in a greater strength than relying on one single model.

The different models of reading and learning stress the importance of motivational conditions which affect the quality of students' cognitive processing (Alexander, 1997, 2017; Vermunt & Donche, 2017). An important motivational condition for text learning is interest (Alexander & Jetton, 1996; Krapp, 1999; Renninger & Hidi, 2011, 2016). Different models of reading and learning from text highlighted the importance of interest for deeper cognitive processing (Alexander, 1997, 2017; Vermunt & Donche, 2017). In the literature on interest, there is a main distinction between individual interest and situational interest (Hidi, 2001; Renninger & Hidi, 2011, 2016). Individual interest refers to a persons' habitual interest in a specific domain, while situational interest is a more short-lived state that is induced by characteristics of the environment (Hidi, 2001; Renninger & Hidi, 2011, 2016; Schiefele, 1999, 2012). There is a debate on whether topic interest is a form of individual interest or situational interest, and some researchers believe it can be an indicator of both types of interest (Hidi, 2001; Renninger & Hidi, 2016; Schiefele, 2012), but both types of interest have a positive influence on the quality of learning (Hidi, 2001). Renninger and Hidi (2011) referred to the work of Schiefele (1996,1999) as a good conceptualization to examine interest in relation to text learning.

Research on topic interest in the field of text learning, has looked into specific sentences of the text that students did, or did not, define as main ideas (McWhaw & Abrami, 2001). The study of McWhaw and Abrami (2001) showed that high-interested students identified the main ideas in the text better than low-interest students. Alexander and Jetton (1996) showed that main ideas in the text are structurally important for text comprehension and that these main ideas are often rated as highly interesting. In addition, other empirical research demonstrated that a higher interest results in a stronger focus on the central ideas in a text (Krapp, 1999; Ryan, Connell, & Plant, 1990). Interest also increases attention and persistence with the learning content (Hidi, 1990, 2000; Krapp, Hidi, & Renninger, 1992).

Previous studies have investigated the relation between topic interest, as a form of individual interest, and deep and surface level learning outcomes, when learning from text (Schiefele, 1996, 1999; Schiefele & Krapp, 1996). Research of Schiefele (1999) and Schiefele and Krapp (1996) indicated that topic interest was related to deep-level learning outcomes, such as deep comprehension, recall of main ideas, elaborations and coherence of recall of main ideas. Krapp (1999) also showed that topic interest was associated with deep processing, both with students' general disposition towards deep processing and with deep processing measured after studying for exams. The strong associations between interest and deep processing may be explained by the fact that deep processing requires more cognitive effort from students and that interested readers are more willing to invest effort in learning than less interested readers (Schiefele, 2012).

1.2. Think-aloud and eye tracking to measure the online learning process

Learning is an ongoing process, and the multidimensional nature of processing can be assessed during the course of this process with online measures (Schellings, 2011; Veenman, 2005). Often used online measures that tap into the text learning process are think-aloud protocols (Fox, 2009; Pressley & Afflerbach, 1995) and eye tracking (Hyönä, Lorch, & Rinck, 2003; Jarodzka & Brand-Gruwel, 2017). Different measures capture different aspects of learning behaviour and all these measures have their advantages and disadvantages. The think-aloud method offers a rich source of data, but it can alter processing itself as students need to perform a learning task and concurrently report on their processing (Ericsson & Simon, 1993; Veenman, 2005). According to Hyönä and Lorch (2004) eye tracking is an attractive method for investigating global text processing in comparison with other online measures because eye tracking collects several indices of processing simultaneously and does not disrupt students' processing. However, eye tracking data still needs to be interpreted by the researcher and to reduce the amount of inferences required by the researcher, eye tracking data can be combined with other types of measures, such as verbal reports (Hyönä, 2010; van Gog & Jarodzka, 2013). Because concurrent reporting can affect eye movement patterns, cued retrospective reporting offers a good alternative in combination with eye tracking (van Gog & Jarodzka, 2013). In cued retrospective reporting, students are shown their eye movements as a cue to verbalize on their learning behavior. Using eye movements as a memory cue may help learners help to recover how they processed elements in the text (Hyönä, 2010; Penttinen, Anto, & Mikkilä-Erdmann, 2013) and if done immediately after reading the text, students are still able to report on their processing (Veenman, 2005). Eye movement data can also be combined with self-report questionnaires that capture students' general disposition towards cognitive processing (Catrysse et al., 2018). Because the different measures capture different aspects of the learning process, it is important to combine different measures in order to get a more comprehensive picture of what is happening during learning (Endedijk & Vermunt, 2013; Vermunt & Donche, 2017).

There is an extensive research base on how to use eye movements in order to examine learning from text (Holmqvist & Andersson, 2017; Hyönä, Lorch, et al., 2003; Jarodzka & Brand-Gruwel, 2017; Rayner, 2009). Good reviews and methodological work in the field showed that first pass and second pass reading times are often used to gain insight into global text processing. First pass reading times are rather unconscious, while second pass reading times are conscious and strategic in nature (Holmqvist & Andersson, 2017; Hyönä, Lorch, et al., 2003; Jarodzka & Brand-Gruwel, 2017; Rayner, 2009). Longer second pass reading or rereading times are an indication of high-level or deeper cognitive processing (Ariasi & Mason, 2011; Holmqvist & Andersson, 2017; Penttinen et al., 2013), strategic attempts to resolve comprehension problems or further text comprehension (Ariasi et al., 2017; Hyönä & Lorch, 2004; Hyönä, Lorch, & Kaakinen, 2002; Hyönä, Lorch, et al., 2003; Kinnunen & Vauras, 1995), and attempts to reinstate information into working memory in order to elaborate or rehearse that information (Hyönä & Lorch, 2004). Eye tracking researchers in the field of text learning, have looked into specific words or sentences of the text that readers/learners did, or did not, process carefully by means of an area of interest (AOI) analysis (Holmqvist et al., 2011; Jarodzka & Brand-Gruwel, 2017). With an AOI analysis, researchers explored whether students reread several AOI's longer than other AOI's. Research focused on processing differences between topic-introducing, topic-medial and topic-final sentences (Ariasi et al., 2017; Hyönä & Lorch, 2004), between relevant and irrelevant parts in the text (Kaakinen & Hyönä, 2005, 2007), between central versus peripheral ideas in the text (Yeari, Oudega, & van den Broek, 2016; Yeari, van den Broek, & Oudega, 2015), and between key sentences and detailed sentences in the text (Catrysse et al., 2018; Catrysse et al., 2016). Findings are rather mixed with regard to differences between topic-introducing, topic-medial and topic-final sentences (Ariasi et al., 2017; Hyönä et al., 2002; Hyönä, Radach, & Deubel, 2003). Eye tracking research has indicated that readers spend more time on relevant than irrelevant parts of the text (Kaakinen & Hyönä, 2007; Kaakinen, Hyönä, & Keenan, 2002) and that readers process central ideas more thoroughly than peripheral ideas in the text (Yeari et al., 2016; Yeari et al., 2015). Up until now, eye tracking research showed no differences in processing key sentences and detailed sentences in relation to students' deep and surface processing (Catrysse et al., 2018).

1.3. Present study

This study aims to extend current research on how the interaction between cognitive (i.e., cognitive processing) and motivational (i.e., topic interest) characteristics shapes the online learning process of students when learning from expository texts. The current models of learning and reading from text stress the importance of motivational conditions for how students learn, and recognize that cognitive characteristics alone are not sufficient to explain differences in the quality of learning (Alexander, 2005, 2017; Vermunt & Donche, 2017). Eye tracking is used to monitor students' online learning and reading process while learning from expository text. Eye tracking data was combined with other measures that tap into the quality of cognitive processing. Because students' general dispositions may influence what they perceive as important in a text (Kirby et al., 2012), we collected information on deep and surface processing with a self-report questionnaire. In addition, through a cued retrospective think-aloud, we asked students to verbalize how they learned from the text in order to capture more information on students' levels of processing during learning. By collecting different measures that capture different aspects of learning behaviour, we gained a more comprehensive understanding of what is going on during the learning process (Endedijk & Vermunt, 2013; Vermunt & Donche, 2017).

First, we aim to clarify in what way individual differences in cognitive processing alone are reflected in reading times. Previous research on students' processing has suggested that students using deep processing focus on the main themes in the text rather than on details and definitions. Students using surface levels of processing, focus on details and definitions rather than the main themes in the text (Dinsmore & Alexander, 2016; Fox, 2009; Pressley & Afflerbach, 1995; Schellings et al., 2012). Longer second pass reading times indicate deeper cognitive processing (Ariasi & Mason, 2011; Holmqvist & Andersson, 2017; Penttinen et al., 2013). Therefore, we expect that students using more deep processing will show higher rereading times for key sentences in comparison with sentences containing details and students using more surface processing will show higher rereading times for detailed sentences in comparison with key sentences.

Second, we address the interaction between topic interest and cognitive processing during the online learning process. As topic interest has been positively associated with deeper levels of learning outcomes (Schiefele, 1996, 1999; Schiefele & Krapp, 1996) and a stronger focus on the main themes in the text (Krapp, 1999; Ryan et al., 1990), and longer second pass reading times indicate deeper cognitive processing (Ariasi & Mason, 2011; Holmqvist et al., 2011; Penttinen et al., 2013), we expect that high-interested students who use more deep processing will show higher rereading times for key sentences (main ideas) in comparison with detailed sentences. Because previous studies did not show a link between surface levels of processing and topic interest (Schiefele, 1996, 1999; Schiefele & Krapp, 1996), we do not expect an interplay between surface processing and topic interest on eye movement measures.

2. Methodology

2.1. Participants

The participants for our study were higher education freshmen in social sciences. First, 449 students completed a questionnaire on their general dispositions towards deep and surface processing strategies. A purposeful sample of students (*N*=42, 29 females) with a variety of reported deep and surface strategy use was selected for the eye-tracking procedure. The procedure for selecting these students is described below (2.4. Analysis). Due to calibration problems and common problems with eye tracking data quality (Holmqvist et al., 2011), data of 31 participants with a mean age of 20.23 (*SD* = 2.12) was available for the analyses. The calibration accuracy was visually inspected together with the replay of eye movements on the text. When the calibration was not successful, or drift occurred, eye movement data were removed from the dataset. The participants received two cinema tickets and informed consent was obtained. All participants had normal or corrected-to-normal vision, reported having no learning disorders, and Dutch was their native language.

2.2. Material and apparatus

2.2.1. Self-report questionnaire on processing strategies

In order to measure students' general disposition towards processing strategies, the ILS-SV questionnaire (Vermunt & Donche, 2017) was administered. The self-report questionnaire contained eight items on surface (e.g., 'I learn definitions by heart and as literally as possible') and eight items on deep processing (e.g., 'I try to understand the interpretations of experts in a critical way'). The reliability for both scales was .75. All items were scored on a 5-point Likert scale. A confirmatory factor analysis was conducted, and a good fit was reached (>.95 for CFI and >.05 for RMSEA). The deep scale contained items on relating and structuring and critical processing, while the surface scale contained items on memorizing and analysing the learning content.

2.2.2. Learning task

Students were asked to study three expository texts on positive psychology in Dutch. Positive psychology was not included in their curriculum, so participants had little prior knowledge on the topic to avoid the confounding effect of prior knowledge. Texts were adapted from the World book of Hope (Bormans, 2015). The topics of the texts were on hope and happiness (414 words), the tyranny of positive thinking (386 words) and music and hope (392 words). Each text consisted of four paragraphs. The three texts were similar on lexical and sentence complexity, as checked with T-Scan (Pander Maat et al., 2014). In addition, three first year students also read the texts and they indicated that the texts were similar and not too difficult for their reading level.

2.2.3. Eye tracking equipment

The Tobii TX300 eye tracker (dark pupil tracking) was used to collect students' eye movements. The eye-tracking component is integrated into a 23-inch TFT monitor with a maximum resolution of 1920 x 1080 pixels. The eye-tracking camera sampled data binocularly at the rate of 300 Hz. A head stabilization system was not required and head movement was allowed (37 x 17 cm). Tobii Technology (Stockholm, Sweden) reported a gaze accuracy of 0.4°, gaze precision of 0.15°, and latency between 1.0 and 3.3. milliseconds for this eye tracker. The eye movements were recorded with Tobii-Studio (3.2) software.

2.2.4. Topic interest

After each text, students' topic interest was measured with a topic interest measure developed by Schiefele (Schiefele, 1990, 1996; Schiefele & Krapp, 1996). The interest scale was comprised of two parts: feeling-related (emotional component) and value-related valences (motivational component). In the first part, participants were asked to indicate how they felt while reading the text (e.g., 'While reading the text I felt …', "stimulated", "engaged", "bored", and "interested"). In the second part, participants were asked to rate the personal meaning of the topic to them (e.g., 'To me personally, the topic is …', "meaningful", "useful", and "worthless"). Each text was rated on these seven items from 1 ("Completely disagree") to 7 ("Completely agree"). For each participant, a topic interest score was calculated by adding the components of feeling-related and value-related valences and taking the average. The topic interest score varies from 1 to 7 and was standardized for further analysis. Prior research showed that this measure of topic interest is one-dimensional and reliable (Schiefele, 1990, 1996; Schiefele & Krapp, 1996). In the present study, a reliability score of .91 was reached for the first text, and .87 for the second and third text (Cronbach's alpha). A confirmatory factor analysis was conducted for the interest measure per text, and a good fit was reached (>.95 for CFI and >.05 for RMSEA).

2.2.5. Cued retrospective think-aloud (CRTA)

The replay of eye movements was analyzed for the last text that the students processed. The CRTA was conducted by using the gaze videos produced by Tobii Studio software (3.2). In the gaze video, a moving red dot represented the point of fixation and the size of the dot was an indication of how long a fixation lasted. The replay was slowed in order to give the participant time to verbalize what they were doing. The researcher instructed students to watch the replay and to explain how they were studying the text and occasionally stopped the video and asked questions about the studying behavior, such as 'Here you fixated a lot, what where you doing?' or 'Here you are going back in the text, what were you doing?'. The retrospective think-aloud was recorded with screencast software to capture both the eye movement replay and the students' verbalizations.

2.3. Procedure

The experiment was conducted individually for each participant during a one-hour session. First, students completed a self-report questionnaire on their general dispositions towards deep and surface processing as a part of orienting entrance tests at the start of the academic year. Informed consent was obtained to use these data. For the eye-tracking procedure, students signed an informed consent as well. They then received written instructions on the screen for the learning task. They were asked to study the texts as if they were preparing for their exams. After that, the eye tracker was calibrated using a nine-point calibration procedure in which students needed to track nine red calibration dots on a plain, grey background. Students were seated about 60 cm from the screen for the calibration and the eye-tracker was recalibrated before each text. Texts were presented one at a time on the screen, so scrolling was not needed. Studying was self-paced and the presentation order of the texts was counterbalanced across participants. After each text, students filled in the questionnaire on topic interest. After studying the last text, a cued retrospective think-aloud was conducted on the last text.

2.4. Analysis

2.4.1. Self-report questionnaire on processing strategies

In order to select the group of 42 students with a variety on deep and surface strategy use, students with different learning profiles were invited for the experiment. Therefore, a person-oriented perspective was applied in order to look for different learning profiles in our sample. In order to identify different learning profiles, we proceeded in two steps and used a combination of hierarchical and non-hierarchical clustering methods (Gore, 2000; Hair, Anderson, Tatham, & Black, 1998; Heikkilä & Lonka, 2006; Vansteenkiste, Sierens, Soenens, Luyckx, & Lens, 2009). In a first step, a hierarchical cluster analysis was carried out in SPSS (SPSS 23), selecting the squared Euclidean distance and Ward's method (Bergman & El-Khouri, 2003; Hair et al., 1998). Solutions ranging from two up to four clusters were explored. On the basis of theoretical grounds, parsimony of the cluster solution and the explanatory power (the cluster solution should explain more than 50% of the variance in its dimensions) (Milligan & Cooper, 1985), the total number of four clusters was selected. In the second step, the initial cluster centers from the hierarchical clustering analysis are used as a non-random starting point in an iterative k-means clustering procedure (Heikkilä & Lonka, 2006; Vansteenkiste et al., 2009).

Similar to the study of Catrysse et al. (2018), four clusters were identified: a surface learning profile, a deep learning profile, an all-low learning profile and an all-high learning profile. A high score on surface processing and a low score on deep processing characterize the surface learning profile. Students with a deep learning profile score high on deep processing and low on surface processing. The all-low learning profile is characterized by low scores on both surface and deep processing. Students with an all-high learning profile use a combination of deep and surface processing strategies. The means and standard deviations are displayed in Table 1 for the 31 students with valid eye movement data. All learning profiles differed significantly from each other with regard to the deep and surface processing scale.

Table 1

Means and standard deviations on deep and surface processing (z-scores) for each profile

		Deep		Surface	
	N	*M*	*SD*	*M*	*SD*
Surface	10	-.82	.73	.28	.71
Deep	6	.96	.65	-.94	.36
All-low	7	-.49	.41	-.81	.65
All-high	8	.76	.68	1.03	.60

2.4.2. Cued retrospective think-aloud

The CRTA's were transcribed from the audiotapes. The CRTA's were coded based on an already developed coding scheme on deep and surface levels of text learning of Dinsmore and Alexander (2016) and on covert cognitive strategies on text learning of Merchie and Van Keer (2014b). Based on conceptual models on learning from text and previous research with think-aloud protocols, we divided the cognitive strategies into deep or surface processing activities (Catrysse et al., 2016; Dinsmore & Alexander, 2016; Pressley & Afflerbach, 1995). Each activity, its description, and an example are displayed in Table 2. In addition, we indicated from which study each code was adapted. The coding schemes of Dinsmore and Alexander (2016) and Merchie and Van Keer (2014b) were more elaborated, but we used only the codes for which we did find evidence in the transcripts. Transcripts were coded with the qualitative analysis software package Nvivo 10. Similar to the study of Dinsmore and Zoellner (2017), we calculated a depth of processing measure by taking the number of deep processing activities divided by the total number of processing activities (surface and deep processing). By calculating this relative measure, we can control for how talkative a student is.

Table 2

Coding scheme on deep and surface processing for the CRTA

Category	Subcategory	Adapted from	Example
Deep processing	Arguing with the text	Dinsmore & Alexander (2016)	'I did not agree with the text content here. The idea that positive thinking can heal cancer is just strange.'
	Elaborating: Activating prior knowledge	Merchie & Van Keer (2014b)	'I just read the title and wonder about the topic of the text.'
	Elaborating: Relating prior knowledge to the text	Merchie & Van Keer (2014b) & Dinsmore & Alexander (2016)	'I was thinking about a presentation from last year and tried to link it to the text.'
	Elaborating: Relating personal experiences to the text	Merchie & Van Keer (2014b) & Dinsmore & Alexander (2016)	'I was reading about optimism and realised that a lot of people say that I am a more pessimistic person.'
	Interpreting	Dinsmore & Alexander (2016)	'I am trying to find the link between the title and this part of the text.'
	Paraphrasing	Merchie & Van Keer (2014b) & Dinsmore & Alexander (2016)	'I tried to summarize the text in my own words.'
Surface processing	Rehearsing	Merchie & Van Keer (2014b) Dinsmore & Alexander (2016)	'I tried to memorize that part, by rehearsing it a few times.'
	Rereading for memorization		'I was rereading that sentence in order to memorize it.'
	Rereading for comprehension		'I was rereading that part in order to comprehend it better.'

2.4.3. Eye movement data

We used the Tobii fixation filter for fixation identification, which is an implementation of a classification algorithm proposed by Olsson (2007). It uses a velocity threshold (35 pixels per window) and a distance threshold (35 pixels) (Olsen, 2012). For each sentence in the text, an area of interest (AOI) was defined. Each sentence in the text was coded as a key sentence, a sentence containing detailed information, or a sentence containing other information. Text 1 contained 22 sentences (Key = 4; Detail = 4; Other = 14), Text 2 consisted of 18 sentences (Key = 4; Detail = 4; Other = 10), and Text 3 counted 19 sentences (Key = 4; Detail = 4; Other = 11). A key sentence is a superordinate sentence that integrates several of the sentences in the paragraph (Hyönä et al., 2002) (e.g., “Hope is the expectation that things will turn out in a good way in the future.”). The detailed sentence code was used when detailed information was given about a concept (e.g., “Recent research shows that 61 % of people have good hopes to reach important goals in their live.”). All the other sentences were coded as sentences containing other information. Two educational researchers coded the sentences according to the definitions and an inter-rater agreement of .89 was reached (Cohens' kappa). When no agreement was reached on the sentence code, the two judges reached consensus about the code through discussion. T-Scan indices indicated that there were no differences between AOI's on lexical and sentence complexity (Pander Maat et al., 2014). In line with eye movement research in reading comprehension (Ariasi et al., 2017; Catrysse et al., 2018; Yeari et al., 2016), first pass and second pass fixation duration were calculated per AOI. To control for the length of AOI's, the eye-tracking measures were normalized by calculating a milliseconds-per-character measure (Ariasi et al., 2017; Catrysse et al., 2018; Yeari et al., 2016).

The eye movement data was analysed with linear mixed effects models (LMM) with the lme4 package (Bates, Maechler, Bolker, & Walker, 2015) in R (R Core Team, 2014) and with the Rstudio interface. The dependent variables for this study are the first pass and second pass fixation duration. Mixed effects models are statistical models that incorporate random and fixed effects (Baayen, 2008; Baayen, Davidson, & Bates, 2008). Subjects, sentences and texts were considered as crossed random effects (Baayen, 2008; Baayen et al., 2008). This means that we were able to jointly generalize our findings to other, similar participants, sentences and texts (Baayen, 2008; Baayen et al., 2008; Quené & van den Bergh, 2008). In addition, the analysis was performed at the sentence level and thus on 1,724 data points, by which mixed effects models offer more power than traditional methods such as ANOVAs (Quené & van den Bergh, 2008). The number of data points is the total number of sentences (59) multiplied by the total number of participants (31). In a next step, fixed effects were added to the models in order to predict eye movement measures. We added fixed effects on the level of each random effect (Table 3). Students' levels of processing were added as a predictor at the subject level, sentence type was added as a predictor at the sentence level and topic interest was added as a predictor at the text level.

Separate models were fitted for the first pass and second pass fixation duration. Three models per measure were fitted: (1) an LMM with students, sentences and texts as random effects and sentence type, topic interest and the score for deep processing (self-report questionnaire) as fixed effects, (2) an LMM with students, sentences and texts as random effects and sentence type, topic interest and the score for surface processing (self-report questionnaire) as fixed effects and (3) an LMM with students, sentences and texts as random effects and sentence type, topic interest and the score for depth of processing (CRTA, see section 2.4.2) as fixed effects. The interactions between the fixed effects were also incorporated into the models.

Table 3

Overview of the random and fixed effects

Random effect	Fixed effect
Subjects	Levels of processing (deep, surface, depth)
Sentences	Sentence type (key, detail, other)
Texts	Topic interest

3. Results

In order to get an overview of the relation between deep processing, surface processing and depth of processing, correlations were computed. There is a moderate positive relation between deep processing and depth of processing (r=.41, p=.02), no significant negative relation between surface processing and depth of processing (r=-.23, p=.21) and no significant negative relation between surface and deep processing (r=-.01, p=.97). The means and standard deviations for the eye movement measures and interest per text are presented in Table 4.

Table 4

Means of first pass fixation duration, second pass fixation duration (in seconds) and interest(non-standardized) by text (standard deviations in parentheses)

	Text 1	Text 2	Text 3

First pass	30.77 (15.77)	31.74 (16.54)	29.09 (15.28)
Second pass	142.81 (78.21)	112.37 (52.46)	113.87 (49.76)
Interest	5.05 (1.06)	5.30 (.99)	5.57 (.93)

3.1. Relations between students' general disposition towards deep processing, interest and eye movement measures

The results for students' general disposition towards deep processing are presented in Table 5. The values of the estimates of the fixed effects reflect the effect of the key and other sentences in comparison with the detailed sentences. Concerning the model for deep processing, parameter estimates indicate that there is no main effect of sentence type on the first pass fixation duration (Key: β=-.04, t=-.18, p=.86; Other: β=.14, t=.79, p=.43). In addition, no main effect is found for deep processing (Deep: β=.14, t=1.44, p=.16). However, there is a significant two-way interaction for sentence type and deep processing (Deep*Keys: β=-.25, t=-2.45, p=.01), meaning that a student who has a higher score on deep processing is looking longer at details than at key sentences during first pass fixation duration. However, first pass fixation durations reflect unconscious behaviour and do not mean that much in terms of strategic eye movement behaviour. For the second pass fixation duration, no significant effects are found for deep processing alone.

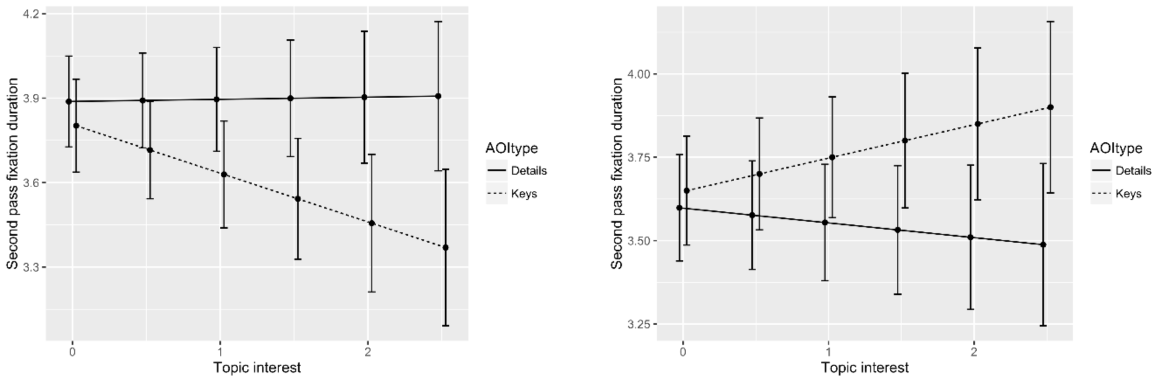
Table 5

Parameter estimates of the random and fixed effects for the random intercept model with deep processing

	First pass fixation duration				Second pass fixation duration			
Random effects	Variance	*SD*			Variance	*SD*		
Student	.16	.40			.23	.48		
Sentence	.22	.47			.04	.20		
Text	.00	.00			.01	.08		
Residual	1.74	1.32			.98	.99		
Fixed effects	β	*SE*	*t*	*pr(>|t|)*	β	*SE*	*t*	*pr(>|t|)*
Intercept	1.66	.17	9.88	**<.001**	3.74	.13	29.94	**<.001**
Interest	.02	.08	.21	.84	-.02	.06	-.32	.75
Deep	.14	.10	1.44	.16	-.14	.10	-1.44	.16
Keys	-.04	.22	-.18	.86	-.02	.11	-.15	.88
Others	.14	.17	.79	.43	-.03	.09	-.34	.74
I*Deep	.05	.07	.71	.48	-.03	.09	-.34	.74
I*Keys	-.04	.10	-.40	.69	-.02	.08	-.24	.81
I*Others	-.15	.08	-1.75	.08	.05	.06	.83	.40
Deep*Keys	-.25	.10	-2.45	**.01**	.07	.08	.88	.38
Deep*Others	-.06	.08	-.77	.44	.05	.06	.86	.39
I*Deep*Keys	-.08	.10	-.77	.44	.16	.08	2.15	**.03**
I*Deep*Others	-.05	.08	-.65	.52	.04	.06	.63	.53

Note: The baseline category is the detailed sentence.

With regard to the interaction between students' levels of processing and topic interest on eye movement measures, there is a significant three-way interaction for sentence type, deep processing and topic interest (Table 5, I*Deep*Keys: β=.16, t=2.15, p=.03). This indicates that when a student scores higher on topic interest and deep processing, this student looks longer at key sentences in comparison with details than a student scoring lower on topic interest and deep processing (Figure 1). This effect on the second pass fixation duration is a reflection of strategic behaviour.



(a) - 1 SD on deep processing (b) + 1 SD on deep processing

Figure 1. Plot of the three-way interaction between topic interest, deep processing and sentence type (y-axis = log of the duration in ms, x-axis = standardized score for topic interest, error bars represent the standard errors).

3.2. Relations between students' general disposition towards surface processing, interest and eye movement measures

With regard to the model for surface processing (Table 6), parameter estimates indicate a significant main effect of surface processing on the first pass fixation duration (Surface: β=.21, t=2.11, p=.04). Students who score higher on surface processing take more time during initial reading than students scoring lower on surface processing. In addition, a significant two-way interaction is found for surface processing and sentence type (Surface*Others: β=-.18, t=-2.25, p=.02), meaning that students scoring higher on surface processing process detailed sentences longer than other sentences during initial reading. With regard to the second pass fixation duration, no significant effects are found. The effects on the first pass fixation duration do not indicate strategic behaviour as we could not find the same effects on the second pass fixation duration.

Table 6

Parameter estimates of the random and fixed effects for the random intercept model with surface processing

	First pass fixation duration				Second pass fixation duration			
Random effects	Variance	*SD*			Variance	*SD*		
Student	.15	.39			.23	.48		
Sentence	.22	.47			.04	.20		
Text	.00	.00			.01	.09		
Residual	1.74	1.32			.98	.99		
Fixed effects	*β*	*SE*	*t*	*pr(>|t|)*	*β*	*SE*	*t*	*pr(>|t|)*
Intercept	1.66	.17	9.95	**<.001**	3.74	.13	28.38	**<.001**
Interest	.02	.08	.24	.81	-.02	.06	-.42	.68
Surface	.21	.10	2.11	**.04**	-.09	.10	-.88	.39
Keys	-.04	.22	-.20	.84	-.01	.11	-.05	.96
Others	.14	.17	.78	.44	-.03	.09	-.34	.74
I*Surface	.06	.07	.83	.41	-.02	.05	-.31	.76
I*Keys	-.05	.10	-.47	.64	-.01	.08	-.11	.91
I*Others	-.14	.08	-1.73	.08	.06	.06	.94	.35
Surface*Keys	-.18	.10	-1.77	.08	.08	.08	1.00	.31
Surface*Others	-.18	.08	-2.25	**.02**	-.01	.06	-.09	.93
I*Surface*Keys	-.04	.10	-.43	.67	-.01	.08	-.17	.87
I*Surface*Others	-.02	.08	-.19	.85	.05	.06	.75	.45

Note: The baseline category is the detailed sentence.

3.3. Relations between students' depth of processing, interest and eye movement measures

The results for the relation between students' depth of processing during text learning and eye movement measures are displayed in Table 7. With regard to the first pass fixation duration, parameter estimates indicate a significant two-way interaction for sentence type and depth of processing (Depth*Keys: β=-.20, t=-1.95, p=.05), meaning that a student who has a higher score on depth of processing is looking longer at details than at key sentences during first pass fixation duration. Concerning the second pass fixation duration, parameter estimates indicate a significant main effect for depth of processing (Depth: β=-.20, t=-2.05, p=.05). Students who score higher on depth of processing, thus take less time for rereading.

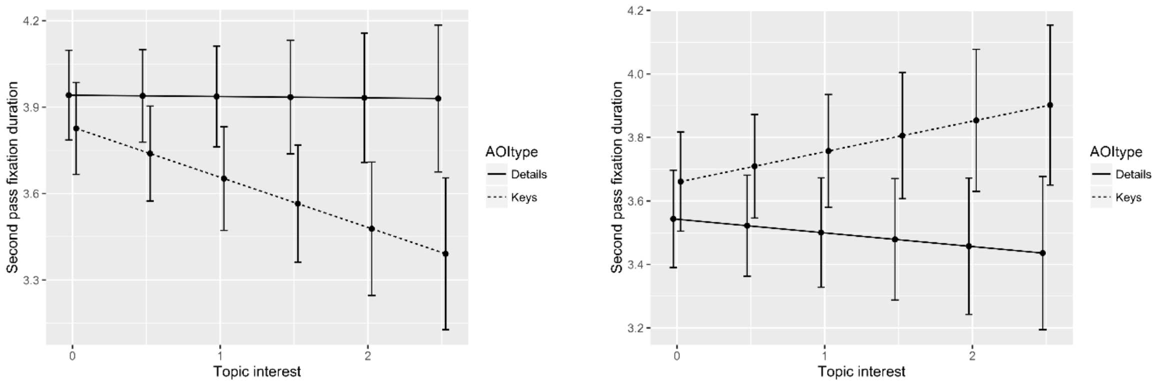
Table 7

Parameter estimates of the random and fixed effects for the random intercept model with depth of processing

	First pass fixation duration				Second pass fixation duration			
Random effects	Variance	*SD*			Variance	*SD*		
Student	.15	.39			.21	.46		
Sentence	.22	.47			.04	.20		
Text	.00	.00			.00	.07		
Residual	1.74	1.32			.98	.99		
Fixed effects	*β*	*SE*	*t*	*pr(>|t|)*	*β*	*SE*	*t*	*pr(>|t|)*
Intercept	1.66	.17	9.98	**<.001**	3.74	.12	31.10	**<.001**
Interest	.03	.08	.45	.65	-.02	.06	-.42	.68
Depth	.14	.10	1.38	.17	-.20	.10	-2.05	**.05**
Keys	-.05	.22	-.20	.84	.0009	.11	.008	.99
Others	.13	.17	.77	.44	-.03	.09	-.28	.78
I*Depth	-.02	.07	-.29	.78	-.02	.05	-.38	.71
I*Keys	-.07	.10	-71	.50	-.01	.08	-.19	.85
I*Others	-.16	.08	-1.89	.06	.06	.06	.89	.37
Depth*Keys	-.20	.10	-1.95	**.05**	.12	.08	1.51	.13
Depth*Others	-.05	.08	-.65	.52	.05	.06	.75	.46
I*Depth*Keys	-.02	.09	-.23	.82	.15	.07	2.19	**.03**
I*Depth*Others	-.05	.08	-.69	.49	.09	.06	1.55	.12

Note: The baseline category is the detailed sentence. Depth of processing is the number of deep processing activities divided by the total number of cognitive processing activities. It encompasses both deep and surface processing.

Concerning depth of processing (Table 7), there is a significant three-way interaction for sentence type, depth of processing and topic interest (I*Depth*Keys: β=.15, t=2.19, p=.03). This indicates that when a student scores higher on topic interest and depth of processing, that this student looks longer at key sentences than details than a student scoring lower on topic interest and depth of processing (Figure 2). This effect reflects strategic eye movement behaviour.



(a) - 1 *SD* on depth of processing (b) + 1 *SD* on depth of processing

Figure 2. Plot of the three-way interaction between topic interest, depth of processing and sentence type (y-axis = log of the duration in ms, x-axis = standardized score for topic interest, error bars represent the standard errors).

4. Discussion

This study investigated the interaction between cognitive processing and topic interest during the online learning process when learning from expository text. Current models of learning and reading from text highlighted the importance of motivational conditions for the quality cognitive processing. In addition, it was emphasized that cognitive characteristics alone are not sufficient to explain differences in the quality of learning (Alexander, 2005, 2017; Vermunt & Donche, 2017). Previous research has investigated cognitive processing during the online process of learning from text (Catrysse et al., 2018; Dinsmore & Alexander, 2016; Fox, 2009) and has examined the interplay between topic interest and cognitive processing at the level of the learning product (Schiefele, 1996; Schiefele & Krapp, 1996). However, the interaction between cognitive processing and topic interest or the multidimensional nature has not been examined before during the online process of learning from text. Even though the learning product is influenced by the learning process, much of the learning takes place during reading and it is thus important to further explore students' online learning process (Kendeou & Trevors, 2012). In our study, we used eye tracking as an online measure to map students' learning and reading behaviour while learning from expository texts and examined the interaction between students' cognitive processing and topic interest on their eye movement measures.

First, we looked at how cognitive processing alone shapes the learning and reading behaviour. More specifically, we examined how individual differences in cognitive processing are reflected in reading times when learning from expository text. In the first step, we investigated the relation between students' general disposition towards deep and surface processing and eye movement measures. Deep processing only affected the first pass fixation duration, students scoring higher on deep processing looked longer at details than at key sentences during initial reading. Results showed that deep processing alone did not affect this second pass fixation duration. However, first pass fixation duration is an indication of early processing and does not reflect strategic or conscious behaviour. Therefore, the second pass fixation duration is the most interesting measure for this study as it reflects strategic and conscious behaviour (Hyönä, Lorch, et al., 2003). If the same effects are found for the first and second pass fixation duration, the first pass fixation can be seen as a pre-effect of the more strategic second pass fixation duration. But a single effect on first pass fixation duration does not mean that much in terms of strategic processing. Students' general disposition towards surface processing also only affected first pass fixation duration with students scoring higher on surface processing looking longer at details than other sentences during initial reading. Students' general disposition towards cognitive processing did not affect rereading. Thus, students reread key sentences, detailed sentences and other sentences for the same amount of time. However, previous research showed that students using deep levels of processing focus more on main themes than details and that students using surface levels of processing focus more on details than main themes. Moreover, longer second pass fixation durations reflect deeper cognitive processing (Ariasi & Mason, 2011; Holmqvist et al., 2011; Penttinen et al., 2013) thus we expected that students scoring higher on deep processing would reread key sentences longer than detailed sentences and students scoring higher on surface processing would reread detailed sentences more than key sentences.

Similar to a previous eye-tracking study, students' general disposition towards cognitive processing does not affect the selectivity in processing different types of sentences in an expository text during rereading (Catrysse et al., 2018). We also examined students' depth of processing during learning from text. Depth of processing, indicated by the number of deep processing activities divided by the total number of cognitive activities, affected the first pass fixation duration. Students scoring higher on depth of processing, looked longer at details than at key sentences during initial reading. In addition, students scoring higher on depth of processing, took less time for rereading the text (i.e., for all sentence types). This could be an indication that these students are more efficient in capturing information from the text, but the link with learning outcomes is needed to gain more information on this relation. To sum up, it can be concluded that cognitive processing alone does not explain differences in the online learning process, because students process the different sentence types in a similar way during rereading, which is an indication of strategic eye movement behaviour.

Second, we examined how topic interest interacts with deep and surface levels of processing during the online learning process. Results showed an interplay between students' topic interest, students' general disposition towards deep processing and eye movement measures for the second pass fixation duration. Students with a high interest for the text and generally using deep processing, reread key sentences longer than detailed sentences. There was no interaction between students' general disposition towards surface processing, topic interest and eye movement measures. In addition, results from the retrospective think-aloud protocols demonstrated the same pattern. Students with high interest for the text and a higher score for depth of processing, reread key sentences longer than detailed sentences. Our hypothesis, that students with a high topic interest and using more deep processing, would reread key sentences more than detailed sentences is thus confirmed by the results. The association in models on reading and learning from text between interest and deep processing (Alexander, 1997, 2017; Vermunt & Donche, 2017), can be explained in our study by the fact that students with a higher interest who use deep processing put more cognitive effort in processing the superordinate sentences in a paragraph that integrate several sentences of a paragraph. This study advances the present knowledge in the field by showing that the interaction between interest and deep processing only increases cognitive effort for these superordinate sentences and not for all information in the texts. Moreover, this study demonstrated the positive relation between topic interest and deep levels of processing during the online learning process.

Although findings from this study provided more insight into the interaction between topic interest, cognitive processing and eye movement measures, this study also has some limitations. First, we did not take into account students' learning outcomes because our main interest was on the learning process. Although students using more deep processing and who have a higher interest in the text, spend more time rereading key sentences than detailed sentences, we do not know if they would recall these main ideas better. However, we expect so because previous research showed positive links between learning outcomes and longer eye fixation durations (Ariasi et al., 2017; Ariasi & Mason, 2011), positive links between deep processing and learning outcomes (Dent & Koenka, 2016) and positive links between topic interest and deep level learning outcomes (Schiefele, 1996, 1999; Schiefele & Krapp, 1996). A second limitation of this study is the relatively small sample size, although the sample is considered sufficient and in line with common eye tracking research designs in the field (Holmqvist et al., 2011). A third limitation of this study is that we did not explicitly measure students' prior knowledge on the text topic. Theoretical models on reading and learning agree that prior knowledge plays an important role in how a student will process the learning material (Alexander, 1997, 2017; Baeten, Kyndt, Struyven, & Dochy, 2010; Vermunt & Donche, 2017). However, recent studies taking both topic interest and prior knowledge into account showed stronger effects of topic interest on learning in comparison with prior knowledge (Dinsmore & Zoellner, 2018; Parkinson & Dinsmore, 2018). A last limitation of this study is that we only looked at the frequency of strategy use for both students' general disposition towards cognitive processing and for their task-specific processing activities. However, a recent review of Dinsmore (2017) demonstrated that how well a strategy is used and how appropriate the chosen strategy is, are better predictors of learning outcomes. It would thus be interesting for future research to move beyond frequency measures.

With regard to analyzing the eye movement data on learning from a text, we want to emphasize the strengths of applying mixed effects models. Although this analytic technique was described in good practices by different researchers (Baayen, 2008; Baayen et al., 2008; Quené & van den Bergh, 2008), it is only very recently that eye tracking researchers have adapted this analysis technique to examine eye movement data on reading/learning from texts, for example, the work of Ariasi et al. (2017). Mixed effects models offer several advantages in comparison with other techniques, such as repeated measures ANOVA (Baayen, 2008; Baayen et al., 2008; Quené & van den Bergh, 2008). A first advantage is that mixed effects models offer more statistical power by conducting analysis on the sentence level instead of on the subject level (Baayen, 2008; Baayen et al., 2008; Quené & van den Bergh, 2008). Furthermore, mixed effects models have a lower risk of capitalization on chance, i.e., type I error (Quené & van den Bergh, 2008). Other advantages of mixed effects models include, among others, better methods for treating continuous responses and better methods for modeling heteroscedasticity and non-spherical error variance. In addition, by treating subjects, sentences and texts as crossed items, results can be jointly generalized over similar subjects, sentences and texts (Baayen, 2008; Quené & van den Bergh, 2008). In addition, individual variability is taken into account by using mixed effects models (Baayen, 2008). Even though we did not take into account a lot of variables at the subject level to explain individual differences, we took this variability explicitly into account in our models. Moreover, by using this analysis technique, this study took a step forward methodologically by moving beyond pure correlational analysis in multi-method designs (Schellings & van Hout-Wolters, 2011; Veenman, 2005).

The overall conclusion of this study is that there is an important interaction between topic interest and deep processing on eye movement measures, for both students' general disposition towards deep processing and depth of processing during learning from expository text. The importance of deep processing has been highlighted for students in higher education and beyond (Vermunt & Donche, 2017), but in addition we want to stress the importance of giving students learning contents that spark their interest (Renninger & Hidi, 2016). This study provided evidence for the multidimensional nature of text learning. More specifically, high-interested students, who use deep levels of processing, reread key sentences in a text for longer than detailed sentences and thus process these key sentences more deeply. This study emphasizes the importance of the interaction between levels of processing and other learner characteristics in order to fully understand the learning process. In addition, it shows that the selectivity in processing different sentences is the result of a more complex interaction between different learner characteristics and is not solely determined by the levels of processing. Although this was already assumed in theoretical frameworks on levels of processing and empirical research focusing on learning outcomes (Alexander & Jetton, 1996; Schiefele, 1996, 1999, 2012; Schiefele & Krapp, 1996), this study is the first to show these effects during the online learning and reading process. Moreover, we demonstrated that general self-report questionnaires can still be valuable to inform us on students' task specific processing when taking into account other task-specific motivational characteristics. Consequently, we strongly advise for future research to further examine the relationship between different learner characteristics and levels of processing in order to unravel the multidimensional nature of learning from a text (Alexander, 2017).

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