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## How are learning strategies reflected in the eyes? Combining results from self-reports and eye-tracking

### Abstract

**Background.** Up until now, empirical studies in the Student Approaches to Learning field have mainly been focused on the use of self-report instruments, such as interviews and questionnaires, to uncover differences in students' general preferences towards learning strategies, but have focused less on the use of task-specific and online measures.

**Aims.** This study aims at extending current research on students' learning strategies by combining general and task-specific measurements of students' learning strategies using both offline and online measures. We want to clarify how students process learning contents and to what extent this is related to their self-report of learning strategies.

**Sample.** Twenty students with different generic learning profiles (according to self-report questionnaires) read an expository text, while their eye movements were registered in order to answer questions on the content afterwards.

**Methods.** Eye-tracking data was analysed with generalized linear mixed effects models.

**Results.** The results indicate that students with an all-high profile, combining both deep and surface learning strategies, spend more time on rereading the text than students with an all-low profile, scoring low on both learning strategies.

**Conclusions.** This study showed that we can use eye-tracking to distinguish very strategic students, characterized by using cognitive processing and regulation strategies, from low strategic students, characterized by a lack of cognitive and regulation strategies. These students processed the expository text according to how they self-reported.

### 1. Introduction

Learning from expository texts is one of the most fundamental skills in our current society and the competence to learn from demanding textbooks is crucial in education and beyond (Clinton & van den Broek, 2012; Mason, Tornatora, & Pluchino, 2013; O'Brien, Cook, & Lorch, 2015). The Student Approaches to Learning (SAL) tradition is mainly interested in how students learn during their academic studies (Gijbels, Donche, Richardson,

& Vermunt, 2014; Vermunt & Donche, 2017). Research within the SAL field goes back to the seminal studies by Marton and his colleagues from the Goteborg research group (Marton & Säljö, 1976). They investigated how students processed academic texts in experimental situations (Marton & Säljö, 1976; Richardson, 2015). Later on, and inspired by this research, a repertoire of self-report questionnaires was developed to quantify individual differences in students' learning strategies (Biggs, 1987; Entwistle & Waterston, 1988). Since the original quasi-experimental work and, with the development of self-report questionnaires, learning strategies have been investigated at different contextual levels, such as the task level, the course level and the general level (over several courses) (Lonka, Olkinuora, & Mäkinen, 2004). However, up to now, empirical studies in the SAL field have primarily been focused on the use of self-report instruments to uncover differences in students' learning strategies at the general level (Fryer, 2017; Lonka et al., 2004; Schellings, 2011).

Although the SAL tradition has roots in experimental work at the task level (Richardson, 2015), empirical research has mainly investigated learning strategies at the general (or departmental) and course level (Fryer, 2017) using self-report questionnaires. In the related field of self-regulated learning (SRL), there is a more extensive research base on how strategies vary depending on the learning situation and task with online measurement tools, such as think aloud protocols, observations and computer trace data (Azevedo et al., 2013; van Gog, Paas, Van Merriënboer, & Witte, 2005; Zusho, 2017). Researchers in the field of SRL have argued that strategy use varies across learning tasks and that general self-reports are thus not always a good predictor of task-specific strategy use (Perry, 2002; Perry & Winne, 2006; Veenman, Bavelaar, De Wolf, & Van Haaren, 2014). However, in the SAL field, there is a lack of research in which task-specific, online measures are adopted to uncover differences in learning strategies. As stated in the review of Vermunt and Donche (2017), empirical research in the SAL field can move forward by investigating the variability of learning strategies on specific task levels versus a more domain and general level. Therefore, a first aim of this study is to combine task-specific and general measurements of students' learning strategies. Although research using self-report questionnaires has been criticised for several reasons, we cannot refrain from using self-report questionnaires in order to be able to capture individual differences in perceptions of student learning. Therefore, we will use eye-tracking as an online measure to map individual differences in reading to learn and compare eye-tracking measures with results from general self-report measures on students' learning strategies. We thus want to clarify if students process the learning material according to how they self-report to process the material. Eye-tracking has a long history in reading research (Jarodzka & Brand-Gruwel, 2017; Rayner, 2009) and has thus established measures in reading

and learning from text. In addition, eye-tracking offers several advantages in comparison with the other online techniques, such as think aloud protocols and observations, because it collects several indices of processing simultaneously and does not disrupt the students' learning behaviour (Hyönä & Lorch, 2004). Therefore, eye-tracking seems to be a promising tool to investigate students' processing strategies in learning from text. A second aim of this study is to examine how eye-tracking measures, adapted from reading comprehension, can inform us on differences in students' learning strategies. The combination of different measures can yield convergent or divergent views on student learning (Endedijk & Vermunt, 2013), which is crucial for further theory building and important to depict a more comprehensive picture of students' learning strategies (Gijbels et al., 2014; Vermunt & Donche, 2017).

## **2. Theoretical framework**

### **2.1. Conceptualisation of learning strategies**

Various models on students' learning strategies in higher education have been developed (Fryer, 2017; Vermunt & Donche, 2017; Zusho, 2017). More specifically, there are distinct American (SRL) and European/Australian (SAL) conceptual frameworks regarding how students learn (Fryer, 2017), but both research traditions describe how and why students process learning content. For reasons of space, we will further elaborate on the conceptualisation of students' learning strategies within the SAL field. In most of the models on student learning in the SAL field, learning strategies are seen as the essential elements of learning (Gijbels et al., 2014; Vermunt & Donche, 2017). Learning strategies can be described as consisting of two components, namely, regulation and cognitive processing (Vermunt & Vermetten, 2004). Regulation strategies refer to the activities that students use to steer their processing strategies (Vermunt & Minnaert, 2003). Applied on learning from text, examples of regulation activities are orienting on the text, monitoring comprehension and diagnosing difficulties in the text (Fox, 2009; Merchie & Van Keer, 2014; Pressley & Afflerbach, 1995). Vermunt and Vermetten (2004) described that students can regulate their learning processes themselves or by instructions from the teacher or learning material. Some students lack regulatory skills (Vermunt & Vermetten, 2004). Processing strategies refer to the cognitive activities that a student applies whilst processing study material (Vermunt & Vermetten, 2004). A main distinction has been made between deep and surface processing strategies (Gijbels et al., 2014; Vermunt & Donche, 2017). Deep processing refers to the intention to understand what the author wants to say in the text,

to engage in meaningful learning, to relate the content of the text to a wider context and prior knowledge and to focus on the main themes and key information in the text. Surface processing, on the other hand, refers to selectively memorizing learning content without looking for meaning, focusing on parts of the text in sequence and to learn details and definitions by heart (Marton & Säljö, 1976; Richardson, 2015; Vermunt & Vermetten, 2004).

With regard to processing strategies, a distinction has been made between deep and surface processing strategies but research indicates that it cannot be seen as a pure dichotomy (Dinsmore & Alexander, 2015; Lonka et al., 2004; Vanthournout, Coertjens, Gijbels, Donche, & Van Petegem, 2013). Students may have a predominant approach (Kember, Leung, & McNaught, 2008; Lonka et al., 2004), but depending on the learning task, students can either use surface strategies, deep strategies or a combination of both (Catrysse et al., 2016; Dinsmore & Alexander, 2015). Thus, some students show all features of one learning strategy, while others are more flexible and show characteristics of more learning strategies (Donche & Vermunt, 2017). Most of the time students combine several strategies while learning and, consequently, how students learn cannot be characterized by one single strategy (Donche & Van Petegem, 2009; Vanthournout et al., 2013). Different learning profiles have already been distinguished, for example, students who mostly use deep strategies, surface strategies, a combination of both and, lastly, students who do not seem to use any of the strategies (Lindblom-Ylänne & Lonka, 1998, 2000; Vanthournout et al., 2013). These learning profiles are also related to students' regulation strategies: students who use a combination of both strategies are often characterized by scoring high on regulation strategies, while students who do not seem to use any of the strategies are characterized by lacking regulatory skills (Donche, Coertjens, & Van Petegem, 2010; Donche & Van Petegem, 2009).

## 2.2. Eye-tracking and learning from text

Eye-tracking has helped us to understand reading processes over the past decades (Rayner, 2009). Jarodzka and Brand-Gruwel (2017) structured eye-tracking research on reading into three levels: (1) reading single words or sentences; (2) reading and comprehending a complete text and (3) reading several text documents. However, most eye-tracking research has focused on reading single words or sentences (for a review see Rayner, 2009). Eye-tracking has also been adopted in level two and level three research on reading comprehension, but to a lesser extent (e.g., Ariasi, Hyönä, Kaakinen, & Mason, 2016; Kaakinen & Hyönä, 2010; Yeari, Oudega, & van

den Broek, 2016). First pass and second pass reading times are often-used eye-tracking measures in global text processing (Jarodzka & Brand-Gruwel, 2017; Hyönä, Lorch, & Rink, 2003). Longer second pass reading times or rereading times are an indication of cognitive conflict (Mikkilä-Erdmann, Penttinen, Anto, & Olkinuora, 2008), high-level or deeper cognitive processing (Ariasi & Mason, 2011; Holmqvist et al., 2011; Penttinen, Anto, & Mikkilä-Erdmann, 2013), strategic attempts to either resolve comprehension problems or further text comprehension (Ariasi et al., 2016; Hyönä & Lorch, 2004; Hyönä, Lorch, & Kaakinen, 2002; Hyönä et al., 2003; Kinnunen & Vauras, 1995), comprehension monitoring (van Gog & Jarodzka, 2013), difficult passages (Rayner, Chace, Slattery, & Ashby, 2006) and attempts to reinstate text information into working memory in order to elaborate on it or rehearse it (Hyönä & Lorch, 2004).

In addition, researchers have also looked into specific words or sentences of the text that participants did, or did not, read carefully by means of AOI (area of interest) analyses (Holmqvist et al., 2011; Jarodzka & Brand-Gruwel, 2017). Researchers looked at differences in processing between topic-introducing, topic-medial and topic-final sentences (Ariasi et al., 2016; Hyönä & Lorch, 2004), differences between relevant and irrelevant parts in the text (Kaakinen & Hyönä, 2005, 2007) and differences between central versus peripheral ideas in the text (Yeari et al., 2016; Yeari, van den Broek, & Oudega, 2015). Findings with regard to topic-introducing, topic-medial and topic-final sentences are rather mixed (Ariasi et al., 2016; Hyönä et al., 2002; 2003).

Concerning the comparison between relevant and irrelevant parts in the text, research has indicated that more time is spent on relevant than on irrelevant parts in the text (Kaakinen & Hyönä, 2007; Kaakinen, Hyönä, & Keenan, 2002). There is also evidence that central ideas, which are important to the overall meaning of the text, are processed more thoroughly than peripheral ideas (van den Broek, Helder, & Van Leijenhorst, 2013; Yeari et al., 2015, 2016). Eye-tracking research indicates that readers spend more time on processing central ideas during the first pass reading and rereading of the text (Hyönä & Niemi, 1990). Research of Yeari et al. (2015) showed that rereading central ideas only takes longer for some reading goals, namely, reading for entertainment and in order to give a presentation compared to reading in order to answer questions on the content afterwards.

Typically, there is a large variability between readers on eye-tracking measures (Jarodzka & Brand-Gruwel, 2017; Rayner, 2009). Jarodzka and Brand-Gruwel (2017) indicated that eye-tracking measures vary according to prior knowledge and ability among others. Eye-tracking research on reading from text showed that readers with large working memory capacity have higher first pass reading times on relevant information than readers with

low working memory capacity (Kaakinen et al., 2002). Low span readers only showed the relevance effect in rereading times. Another study of Kaakinen, Hyönä and Keenan (2003) showed that readers with prior knowledge and a high working memory capacity encode relevant information into memory without extra processing time. Some studies have controlled for prior knowledge in order to ensure that readers do not differ on prior knowledge in different reading conditions (e.g., Ariasi et al., 2016; Ariasi & Mason, 2011).

### 2.3. Present study

This study aims at extending current research on learning strategies in the SAL field by combining offline and online measures at a general and task-specific level. Previous research showed lower, but still convergent, validity between self-reported general and task-specific measures (Endedijk & Vermunt, 2013; Veenman, 2005; Veenman, Prins, & Verheij, 2003). Self-reports raises questions about the learners' abilities to reflect on and verbalise cognitive processes (Penttinen et al., 2013) and, therefore, eye-tracking offers an alternative measure, away from self-reports, to monitor online comprehension processes. In addition, research has already indicated that individual differences, such as working memory capacity and prior knowledge, are reflected in eye-tracking measures (Kaakinen et al., 2002; 2003), but so far no attempt has been made to test whether individual differences in learning strategies can be reflected in eye-tracking measures. Therefore, two research questions are central in this study: (1) In what way do students who self-reported to use deep strategies, show higher rereading times? As described in the theoretical framework, longer second pass reading times are an indication of deeper cognitive processing and attempts to resolve comprehension problems (Ariasi & Mason, 2011; Holmqvist et al., 2011; Penttinen et al., 2013; van Gog & Jarodzka, 2013). Thus, our hypothesis is that students scoring highly on deep strategies will show higher rereading times. Answers on this research question can provide more insight into how eye-tracking measures offer convergent or divergent evidence for the self-reported strategy use. Research using self-report measures has suggested that students using a deep learning strategy focus on essences and key aspects in the text, while students using a surface learning strategy focus on learning details and definitions (Marton & Säljö, 1976; Vermunt & Vermetten, 2004). Therefore, interesting AOI's are key sentences and sentences containing details in a text and one more research question is central in this study: (2) In what way do students, with different learning profiles, show different reading times (first pass and second pass) for key sentences, detailed sentences and other sentences? If learning strategies influence early on in reading to learn, it will affect the first pass reading time and if it influences the integration of information

more, it will affect the rereading time (Hyönä et al., 2003). Our hypothesis is that students who reported using deep strategies and less surface strategies, will show higher reading times for key sentences in comparison with other and detailed sentences. For students who reported using surface strategies and less deep strategies, our hypothesis is that they will show higher reading times for detailed sentences in comparison with other and key sentences. By answering these research questions, we want to clarify how students process information in texts, and to what extent this is related to their perceptions on learning strategies. In this way, we want to track the rich history of self-report questionnaires back to the inception of the SAL field, which has its roots in reading and learning from academic texts (Richardson, 2015).

### **3. Methodology**

#### **3.1. Participants**

Twenty first year psychology students participated in the eye-tracking study. All students had normal or corrected to normal vision, participated on a voluntarily basis and informed consent was gathered.

#### **3.2. Procedure**

Students were asked to study an expository text on a course interest related topic that was not part of the curriculum, namely, research on positive psychology. The text (774 words) was selected and adapted from the Dutch version of 'The World Book of Happiness' (Bormans, 2010). By written instructions on the screen, students were asked to study the text in order to answer questions on the content afterwards. No information was given on what type of questions they would receive. They received questions about details in the text and questions on deeper comprehension (e.g., give a short summary of the text in your own words). The task was tested in a pilot study with five students. While studying the text in a self-paced manner, students' eye movements were registered. The complete text could be processed on one screen, so scrolling was not needed. After processing the text, students were asked whether they had any prior knowledge on the topic and all students indicated it was a new topic for them.

The Tobii TX300 eye tracker (dark pupil tracking) was used. The eye-tracking component was integrated into a 23-inch TFT monitor with a maximum resolution of 1920 x 1080 pixels. The eye-tracking camera sampled data binocular 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° and gaze precision of 0.15°. The eye tracker latency was between 1.0 and 3.3 milliseconds. Eye movements were recorded with Tobii-Studio (3.2) software. Before starting the experiment, the students' eye movements were calibrated. For the calibration, students were seated about 60 cm from the screen and a five-point calibration procedure was used in which students needed to track five red calibration dots on a plain, grey background. When the calibration was successful, the eye-tracking procedure was started.

Each sentence in the text was coded as a key sentence ( $n = 10$ ), a sentence containing detailed information ( $n = 7$ ) and the remaining sentences were coded as a sentence containing other information ( $n = 29$ ). A key sentence is a superordinate sentence that integrates several of the sentences in the paragraph (Hyönä et al., 2002). The detailed sentence code was used when detailed information was given about a concept. All the other sentences were coded as sentences containing other information. Three judges coded the sentences in the text and an inter-rater agreement of 52 % was reached (Fleiss' kappa), which is considered as moderate. For the sentences where no agreement was reached, the three judges reached a consensus through discussion. We compared the different AOI's in the text on lexical and sentence complexity measures in T-scan (Table 2) (Pander Maat et al., 2014). The results indicate that there was no difference between AOI's on lexical complexity. With regard to sentence complexity, post hoc Tukey contrasts indicated that key sentences were significantly longer than sentences containing other information, but they were not more difficult (D-level). Thus, we can be sure that when students look differently at these AOI's, it is not due to differences in complexity of the sentences, as the measures will be normalized for length.

In line with eye-tracking research in reading comprehension (Ariasi et al., 2016; Hyönä & Lorch, 2004; Hyönä et al., 2003; Yeari et al., 2016), first pass fixation duration, second pass fixation duration and total fixation duration were calculated per AOI (Table 3). To control for the length of AOI's, the eye-tracking measures were normalized by calculating a milliseconds per character measure (Hyönä & Lorch, 2004; Hyönä et al., 2002; Kaakinen & Hyönä, 2005; Yeari et al., 2015). We used the Tobii fixation filter for fixation identification, which

is an implementation of a classification algorithm as proposed by Olsson (2007). It uses a velocity threshold (35 pixels/window) and a distance threshold (35 pixels) (Olsen, 2012).

### 3.3. Analysis

Eighty students completed the Inventory of Learning Patterns – Short Version (ILP-SV) (Coertjens, Donche, De Maeyer, Vanthournout, & Van Petegem, 2012; Donche & Van Petegem, 2008). The self-report questionnaire contained eight items on deep and eight items on surface strategies; items were scored on a 5-point Likert scale. The reliability of the scales is given in Table 1. A confirmatory factor analysis was conducted and a good fit was reached for the main scales of learning strategies ( $>.95$  for CFI and  $<.05$  for RMSEA). In order to select 20 students, a hierarchical cluster analysis was carried out in SPSS (SPSS 23), selecting the squared Euclidean distance and Ward's method (Bergman & El-Khoury, 2003; Hair, Anderson, Tatham, & Black, 1998). Given the higher reliability of the main scales, learning profiles were identified based on the main scales' deep and surface processing. 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), four clusters were selected.

The eye-tracking data was analysed with generalized linear mixed effects models (GLMM) with the lme4 package (Bates, Maechler, Bolker & Walker, 2015) in R (R Core Team, 2014) with the Rstudio interface. Mixed effects models are statistical models that incorporate random and fixed effects (Baayen, 2008; Baayen, Davidson & Bates, 2008; Snijders & Bosker, 1999). Subjects and sentences are considered as crossed random effects (Baayen, 2008; Baayen et al., 2008). This is relevant for our research, because we wish to jointly generalize our findings to other participants and sentences (Baayen, 2008; Baayen et al., 2008; Quené & van den Bergh, 2008). By using mixed effects models, we were able to take into account the variability in students and sentences (Baayen, 2008; Baayen et al., 2008) and these models captured the within-participant correlation among sentences (Quené & van den Bergh, 2008). In addition, the analysis was performed at the sentence level and thus on 920 data points (Table 4), by which mixed effects models offer more power than traditional methods such as ANOVA's (Quené & van den Bergh, 2008).

Eye-tracking duration measures were heavily skewed (Baayen, 2008; Hoffman & Rovine, 2007; Holmqvist et al., 2011). In order to deal with the skewness, the data can be logarithmically transformed (Baayen, 2008; Baayen et al., 2008; Hoffman & Rovine, 2007; Lo & Andrews, 2015) or non-normal distributions can be incorporated into statistical models (Holmqvist et al., 2011; Lo & Andrews, 2015). To check the distribution of the dependent measures, the *fitdistrplus* package (Delignette-Muller & Dutang, 2015) was used. In a first step, a Cullen and Frey graph was made for each duration measure (Figure 1, left). In a next step, the distribution was fitted on the empirical data (Figure 1, right). Fit was assessed graphically and the gamma distribution fitted all dependent measures the best, compared to the normal and lognormal distribution. Therefore, we used GLMM's with the gamma distribution (log link).

Separate models were fitted for the first pass, second pass and total fixation duration. The models included random effects for subjects and sentences, and fixed effects for the sentence type and learning profile. The factual sentence served as the baseline for the comparison between sentence types. The all-low learning profile acted as the baseline for the comparison between the different learning profiles. In order to compare the different sentence types and learning profiles with each other, multiple comparisons of means (Tukey contrasts with bonferroni correction) were calculated using the *multcomp* package (Bretz, Hothorn & Westfall, 2011). In a first step, we fitted a null model (Hoffman & Rovine, 2007; Peugh, 2010; Snijders & Bosker, 1999). In a next step, the fixed effects (sentence type and learning profile) were added to the models. In a last step, the interactions between the fixed effects were added in a new model. Likelihood ratio testing was used to compare the models, with and without interaction terms, between the fixed effects (Peugh, 2010).

#### **4. Results**

In order to analyse the eye-tracking data, we first identified learning profiles based on the self-report questionnaires. Four learning profiles were identified: the all-low, surface, deep and all-high profile (Table 5). An all-low profile is characterized by low scores on both deep and surface processing, a surface profile by a high score on surfacing processing and a low score on deep processing, a deep profile by a high score on deep processing and a low score on surface processing and an all-high profile by high scores on both deep and surface processing (Figure 2). ANOVA tests indicated that the learning profiles differed significantly on deep ( $F(3,16)=14.78, p < .001$ ) and surface strategies ( $F(3,16)=50.87, p < .001$ ) from each other. Tukey post hoc

comparisons with bonferroni correction showed that, with regard to the deep dimension, all learning profiles differed significantly from each other except for the all-high and deep profile (both high on deep) and for the all-low and surface profile (both low on deep). Concerning the surface dimension, only the all-low and the deep profile (both low on surface) and the surface and all-high profile (both high on surface) did not differ significantly from each other.

The learning profiles and sentence types were added as fixed effects in the GLMM's. The estimates for the variance components of the portioned variance of the outcome are displayed in Table 6, and for the fixed effects in Table 7. The values of the estimates of the fixed effects reflect the effect of the deep, all-high and surface profile in comparison with the all-low profile and of the key and other sentences in comparison with the detailed sentences. With regard to the first pass fixation duration, the models with or without interaction terms between the fixed effects did not differ significantly ( $\chi^2(6)=1.82, p>.05$ ). For the reason of parsimony, we selected the model without interaction terms, as none of the interaction terms reached significance. Parameter estimates indicated that there was no main effect of sentence type on the first pass fixation duration (Key:  $\beta=.19, z=.79, p=.43$ ; Other:  $\beta=.31, z=1.47, p=.14$ ). In addition, no main effect was found for the learning profile (Deep:  $\beta=.13, z=.41, p=.68$ ; All-high:  $\beta=-.45, z=-1.27, p=.20$ ; Surface:  $\beta=.04, z=.13, p=.90$ ), students with different generic learning profiles did not differ in their reading times during initial processing (Figure 3).

Similar to the first pass fixation duration, the model with and without interaction terms between the fixed effects did not differ significantly for the second pass fixation duration ( $\chi^2(6)=3.11, p>.05$ ), so, for reasons of parsimony, the results of the model without interaction terms are presented. Similar to the first pass fixation duration, there was no main effect of sentence type (Figure 4). However, we found a main effect of the learning profile. Tukey post hoc comparisons with the bonferroni correction showed that students with an all-high learning profile looked back longer on all types of sentences than students with an all-low learning profile ( $p=.02$ ). This higher rereading time is an indication of deeper processing and/or comprehension monitoring.

Concerning the total fixation duration, the model without interaction terms between the fixed effects was the most parsimonious model ( $\chi^2(6)=5.26, p>.05$ ). Similar to the first pass fixation duration and second pass fixation duration, no main effect of sentence type was found (Figure 5). For the total fixation duration, a main effect of

the learning profile was found, but after bonferroni correction for multiple comparisons, none of the differences between learning profiles remained significant.

## **5. Discussion and conclusion**

The present study aimed at gaining more insight into students' learning strategies when they were learning from an expository text by combining general self-report questionnaires with task specific eye-tracking data. This study aimed to be innovative in at least two ways. First, this study has moved the SAL field forward by investigating the variability of learning strategies on a specific task versus a general level (Vermunt & Donche, 2017). Second, eye-tracking was used as an online and non self-report measure to monitor students' learning processes. As eye-tracking research has a long history of research in reading, it therefore offers already established eye-tracking measures to examine learning from text (Jarodzka & Brand-Gruwel, 2017; Hyönä et al., 2003). Eye-tracking also showed differences in processing with regard to individual differences (Kaakinen et al., 2002; 2003), but so far differences in students' learning strategies were not examined. The combination of different measures at different contextual levels can yield convergent or divergent views on student learning, which is crucial for the further conceptual clarification of learning strategies and a comprehensive view on students learning (Endedijk & Vermunt, 2013; Vermunt & Donche, 2017).

We examined students' eye-tracking data according to their general learning profiles. Similar to previous research, four learning profiles were discerned: all-low, all-high, deep and surface learning profiles (Lindblom-Ylänne & Lonka, 1998, 2000; Vanthournout et al., 2013). The first research question aimed to clarify whether students, who reported using deep learning strategies, showed higher rereading times. We can conclude that very strategic students (all-high learning profile) could be distinguished from low strategic students (all-low learning profile) with eye-tracking measures. All-high students, who reported using both deep and surface strategies, took more time to reread the text than students with an all-low learning profile. Based on previous eye-tracking research on rereading times, we can conclude that all-high students show more deep cognitive processing and comprehension monitoring during learning from expository text (Ariasi & Mason, 2011; Ariasi et al., 2016; Holmqvist et al., 2011; Penttinen et al., 2013). However, students with a deep learning profile did not differ from students with a surface learning profile. This may indicate that eye-tracking measures are not influenced by the quality of a cognitive learning strategy, namely deep and surface learning strategies but only by the quantity of

strategy use, namely high versus low. In addition, we also believe that this study shows the interplay between cognitive processing and regulation strategies as reflected in the eye-tracking measures. All-high learners are often characterized by scoring high on regulation strategies, while all-low students are characterized by lacking regulatory skills (Donche et al., 2010; Donche & Van Petegem, 2009). As rereading time seems both sensible for deeper cognitive processing and comprehension monitoring (Ariasi & Mason, 2011; Ariasi et al., 2016; Holmqvist et al., 2011; Penttinen et al., 2013), this may be the reason why we can only distinguish between all-high (characterized by both cognitive strategies and regulation strategies) and all-low students (characterized by a lack of cognitive and regulation strategies).

The second research question aimed to shed light on how students with different learning profiles, show different reading times for key, detailed and other sentences. Based on the results of the general self-report questionnaires, we expected that students who scored high on deep processing strategies would focus more on the essences in the text and students who scored high on surface processing strategies would focus more on facts and details in the text (Donche & Van Petegem, 2008; Vermunt & Vermetten, 2004). Students with an all-high an all-low learning profile showed no differences in processing key, detailed and other sentences. As these students either scored high or low on both strategies, this was in line with what we would expect from theory. However, students with a deep profile scored high on deep and low on surface strategies, and they also processed key sentences and detailed sentences for the same amount of time. Also, students with a surface learning profile, who reported using more surface than deep strategies, did not show differences in processing time between key and detailed sentences. Thus it seems that students with a deep and surface profile spend the same amount of time on different sentence types when learning from text. This may be an indication that what students report to usually do when learning, is actually not happening this way when they are learning from text. At least not when they study an expository text at one point in time. For future research, it would be interesting to give students the same text at different time points, in order to investigate whether they look differently at key sentences, detailed sentences and other information later in time. It seems plausible that these effects are only visible at later points in time than already from the beginning, when they need to get familiar with the text topic. Differences in reading time can also be influenced by the reading or learning goal (Yeari et al., 2015). We instructed students to read the text in order to answer questions on the content afterwards. Research of Yeari et al. (2015) has already indicated that students did not process central and peripheral ideas differently when they were instructed to answer questions on the content afterwards. However, they did process central and peripheral ideas differently

when they were reading for entertainment or in order to give a presentation afterwards. For future research, it would thus be interesting to give students different reading tasks and reading goals as well. Another reason why we did not detect differences between sentence types, which is a strength of our analysis, is that we did not aggregate on sentence type but added sentences as random effects in the mixed effects models by which the chance for false positives decreases (Quené & van den Bergh, 2008). So, if we generalize to other sentences, no differences can be found between key, detailed and other sentences. Although it is important to generalize over sentences (Baayen et al., 2008; Quené & van den Bergh, 2008), other eye-tracking research has often not taken this into account, except for the study of Ariasi et al. (2016).

Based on this study, we can conclude that rereading time can be used to distinguish between all-high and all-low students. In addition, we can conclude that students with different learning profiles spend the same amount of time on processing keys, details and other information in the text when they need to answer questions on the text afterwards. Although findings from this study contribute to the SAL field, this study also has some limitations. First, students needed to process the text on a computer screen to be able to use the eye-tracking equipment. This does not reflect the natural setting in which students normally process learning contents (Catrysse et al., 2016). A second limitation of this study is that we were not able to explain why students with different learning profiles processed the text differently and why students within a learning profile processed the different sentence types in the same way. By linking the results of general self-report questionnaires to the eye-tracking data, we gained more insight into the quantity of learning strategies and not into the quality. As a further step when investigating learning strategies, we advise for future research to conduct a similar eye-tracking study followed by a retrospective think aloud in order to get more information on the reasons for processing behaviour (Catrysse et al., 2016; van Gog & Jarodzka, 2013), which can refer to important motivational and/or regulatory conditions that need to be present in order to understand the quality of learning strategies. The higher rereading time we found in this study is an indication of deeper processing and/or comprehension monitoring, but a retrospective think aloud can provide more insight into the nature of these cognitive and metacognitive learning activities. Furthermore, a path for future research is to include self-report questionnaire items on regulation strategies as well. Another limitation of this study is that we did not analyse students' learning outcomes because our main interest was on the learning process rather than on the learning outcome. However, it would be interesting to take learning outcomes into account in future research in order to analyse the relationship between learning strategies, eye-tracking measures and learning outcomes. Other research has already shown links between learning

outcomes and eye-tracking measures (e.g., Ariasi et al., 2016; Ariasi & Mason, 2011), as well as between learning strategies and learning outcomes (Dent & Koenka, 2016). Despite these limitations, we also want to emphasize the statistical strength of this study. We used generalized linear mixed effects modelling to analyse the data and by doing that we were able to generalize findings over other students and sentences (Baayen, 2008; Baayen et al., 2008; Hoffman & Rovine, 2007). This is important, because we sampled both students and sentences from a larger population (Quené & van den Bergh, 2008). By applying mixed effects models, the power was raised as well (Baayen et al., 2008; Quené & van den Bergh, 2008). Only twenty students participated in this eye-tracking study, but the learning profiles differed significantly from each other on deep and surface processing. If general self-report questionnaires are an indication of students' task-specific learning strategies, we would be able to see it in the eye-tracking data. Although we had more than a sufficient number of data points for the analysis done in the present study, we strongly suggest to replicate this study and to include more participants since this is one of the first studies to unravel the relation between self-reported learning strategies and eye-tracking. We also advise to add more than one text in the study in order to be able to generalize the findings over several texts as well.

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## **Appendix**

Key sentences in bold

Detailed sentences in italics

**There is a clear pattern between countries: happiness is found in countries with good living conditions.**

*The average score for happiness was 6.64 (scale from 0 to 10). Overall, people are happier in rich, free, tolerant countries with a good government and with high social capital. Consequently, countries such as Finland (7.87), Switzerland (7.42) and Sweden (7.49) had a high score for happiness, while countries such as Bulgaria (4.43), Iraq (3.79) and Zimbabwe (3.24) had lower happiness scores. The position of Belgium in the happiness ranking is, thus, not a surprise. The conditions that lead to a higher happiness score also make the gap in happiness between people in a country smaller. What can we learn from that?*

Table 1

*ILP-SV subscales and main scales, number of items, item example and reliability*

Scale	Items	Item example	Cronbach's Alpha
<i>Deep processing</i>	8		.72
Relating and structuring	4	I compare conclusions from different teaching modules with each other.	.60
Critical processing	4	I try to understand the interpretations of experts in a critical way.	.64
<i>Surface processing</i>	8		.71
Analysing	4	I study each course book chapter point by point and look into each piece separately.	.70
Memorizing	4	I learn definitions by heart and as literally as possible.	.60

Table 2

*Comparison of the different AOI's on lexical and sentence complexity (ANOVA)*

	Factual sentence		Key sentence		Other sentence		ANOVA		
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>F</i>	<i>p</i>	$\eta_p^2$
<b>Lexical complexity</b>									
Word length (number of letters per word)	5.51	1.30	5.43	.57	5.47	.96	.02	.99	.00
Word frequency log	4.59	.65	4.81	.37	4.74	.49	.43	.65	.02
Lemma frequency log	4.72	.63	4.94	.41	4.91	.49	.46	.63	.02
<b>Sentence complexity</b>									
Sentence length (number of words per sentence)	17.57	7.18	21.80	7.19	14.72	6.84	3.9	<b>.03</b>	.15
D-level	1.86	1.68	4.20	2.35	2.31	2.44	2.94	.06	.12

Table 3

*Overview of eye tracking measures and definitions*

Measure	Definition
First pass fixation duration	The time spent in an AOI when it was visited for the first time. A visit can consist of more fixations. It reflects early processing and object recognition.
Second pass fixation duration	Duration of all the regressions back to an AOI. It reflects delayed processing, for example to integrate information.
Total fixation duration	The time spent in an AOI during the whole trial, it is the sum of the first pass fixation time and the second pass fixation time in that AOI.

Table adapted from Catrysse et al. (2016) and definitions adapted from Holmqvist et al. (2011) and Hyönä et al. (2003).

Table 4

*Number of data points in the analysis per learning profile and per sentence type*

Learning profile	Sentence type	Number of data points	Total number of data points
All-low	Details	42	276
	Key	60	
	Other	174	
Surface	Details	35	230
	Key	50	
	Other	145	
Deep	Details	35	230
	Key	50	
	Other	145	
All-high	Details	28	184
	Key	40	
	Other	116	

Table 5

*Means and standard deviations on the main scales (z-score and Likert score (maximum 40)) for each cluster*

	Deep		Surface		
	<i>N</i>	z-scores	Likert	z-scores	Likert
All-low	6	-1.14 (.77)	20.40 (3.91)	-.74 (.12)	23.60 (.55)
Surface	5	-.42 (.50)	24.00 (2.55)	.94 (.28)	31.00 (1.22)
Deep	5	.60 (.54)	29.17 (2.71)	-.91 (.36)	22.83 (1.60)
All-high	4	1.06 (.26)	31.50 (1.29)	1.12 (.50)	31.75 (2.22)

Table 6

*Parameter estimates of the variance components of the partitioned variance of the outcome for the random intercept model*

	FPFD		SPFD		TFD	
	$\beta$	<i>SD</i>	$\beta$	<i>SD</i>	$\beta$	<i>SD</i>
Variance between students	.27	.52	.04	.19	.03	.16
Variance between sentences	.21	.46	.01	.07	.01	.08
Residual variance	1.03	1.01	.45	.67	.29	.54

Table 7

*Parameter estimates of the fixed effects for the random intercept model*

	First pass fixation duration				Second pass fixation duration				Total fixation duration			
	$\beta$	<i>SE</i>	<i>z</i>	<i>pr(&gt; z )</i>	$\beta$	<i>SE</i>	<i>z</i>	<i>pr(&gt; z )</i>	$\beta$	<i>SE</i>	<i>z</i>	<i>pr(&gt; z )</i>
Intercept	1.97	.30	6.55	<b>&lt;.001</b>	3.57	.15	23.88	<b>&lt;.001</b>	3.81	.14	27.89	<b>&lt;.001</b>
Key	.19	.25	.79	.43	-.09	.10	-.89	.37	-.03	.08	-.41	.68
Other	.31	.21	1.47	.14	-.09	.08	-1.01	.31	-.02	.07	-.23	.82
Deep	.13	.32	.41	.68	.13	.18	.75	.45	.10	.17	.58	.56
All-high	-.45	.35	-	.20	.58	.20	2.95	<b>&lt;.01</b>	.41	.18	2.21	<b>&lt;.05</b>
			1.27									
Surface	.04	.33	.13	.90	.46	.19	2.47	<b>&lt;.05</b>	.35	.17	2.03	<b>&lt;.05</b>

Uncorrected p-values are presented in this table. The p-values obtained after controlling for multiple comparisons (Bonferroni correction) are presented in the text.

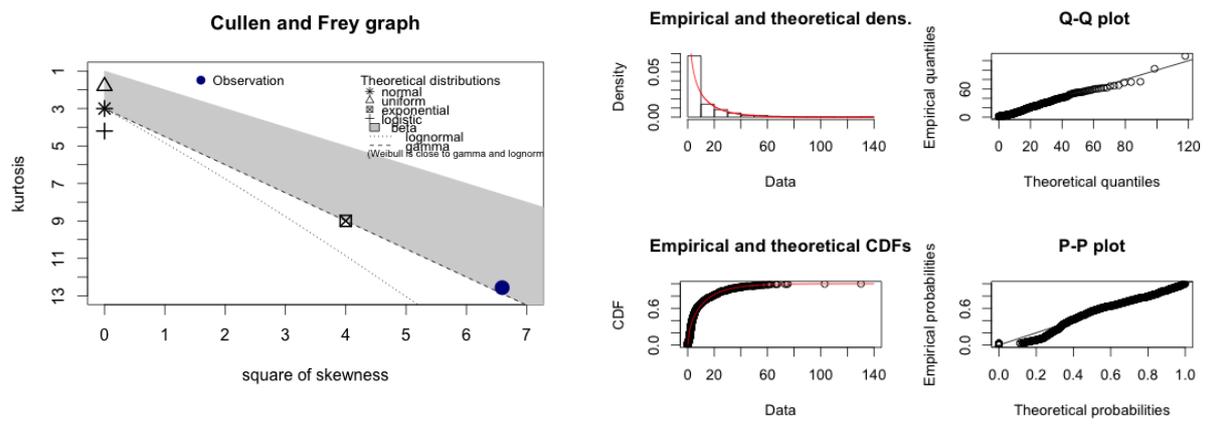


Figure 1. Distribution of the first pass fixation duration (ms/char)

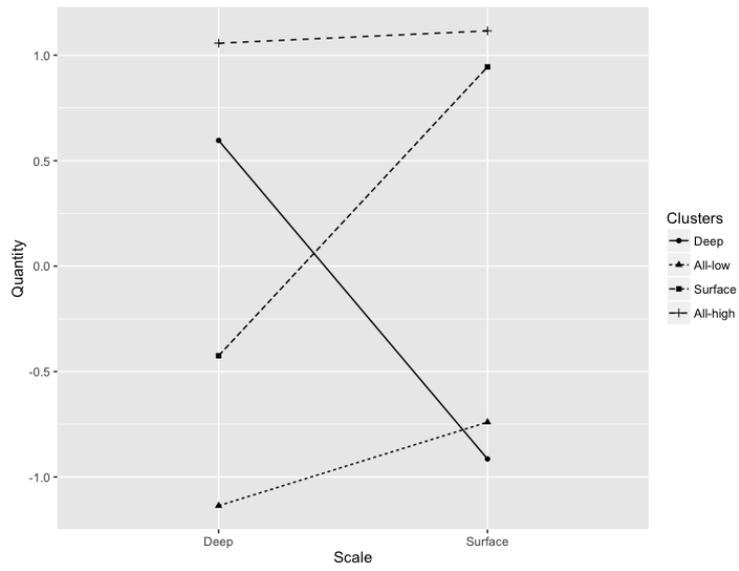


Figure 2. Plot of the four learning profiles and their scores on deep and surface strategies (z-scores).

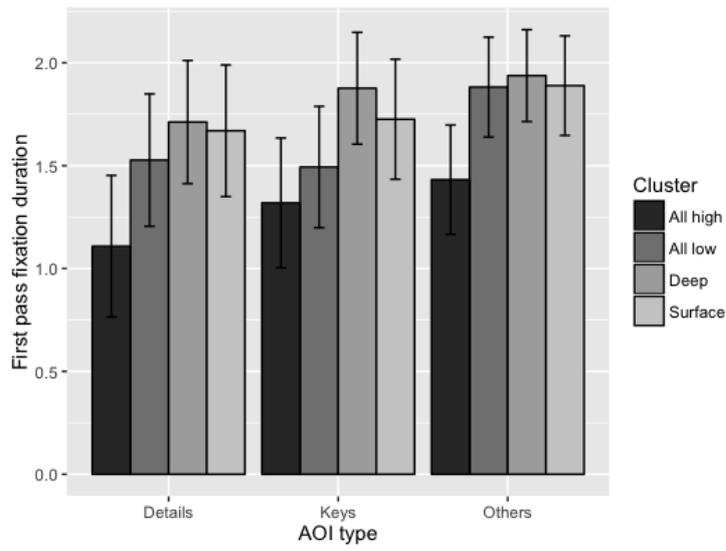


Figure 3. Estimated means and standard errors of the log of the first pass fixation duration (ms/char) for each learning profile per sentence type

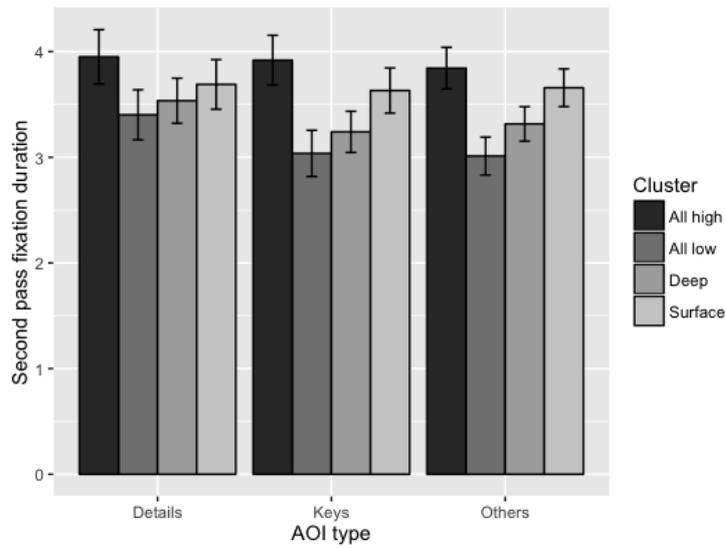


Figure 4. Estimated means and standard errors for the log of the second pass fixation duration (ms/char) for each learning profile per sentence type

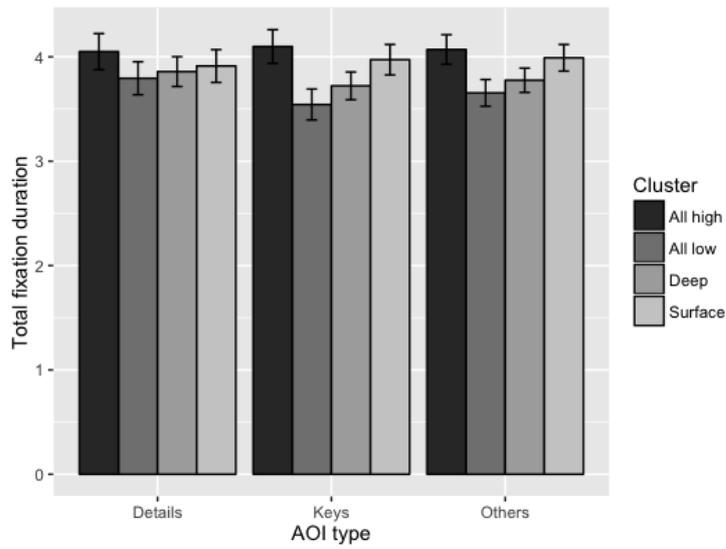


Figure 5. Estimated means and standard errors for the log of the total fixation duration (ms/char) for each learning profile per sentence type