Tracking Estimated Attention Levels During Oral Character String Reading

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Abstract. Cognitive workload during the oral reading of character strings was evaluated using microsaccade (MS) rates and pupillary changes from an open dataset. The data consisted of four types of character strings under both short and long length conditions. Both binocular MS rates and pupillary sizes were chronologically summarised at 500 ms intervals. Analysis revealed that string length significantly affects the temporal changes in both metrics. To uncover the latent reactions to workload, a modelling technique was applied to both metrics to evaluate attentional levels across task conditions. Finally, the underlying cognitive dynamics during oral reading tasks are discussed on these estimated attentional changes.

Keywords: oral reading · cognitive workload · binocular microsaccade · pupil size · modelling

1 Introduction

The reading process has long been studied as a high-level human activity to better understand reading ability and comprehension [13]. Furthermore, the development of reading proficiency is frequently discussed in the context of non-native language acquisition [14, 8]. Because reading is deeply rooted in perceptual and cognitive mechanisms, researchers often measure neurobiological systems to retrieve latent cognitive signatures [4, 17]. Eye-tracking techniques, in particular, are conventionally used to observe the reading process in both silent and oral reading contexts [27], as eye movements occur in direct response to cognitive processing during text engagement. In reading-aloud tasks, the duration of cognitive processing can be observed alongside eye-movement behaviours, such as fixations. This dynamic relationship is known as the eye-voice span (EVS), which is recognised as an index of working memory and cognitive workload [19, 34]. Cognitive activity during oral reading is notably more pronounced than in silent reading, as evidenced by longer fixation durations and total viewing times [19]. Even when single character strings are presented, eye-movements metrics such as fixation and saccades remain accessible for analysis [9]. Furthermore, event-related potential (ERP) study using single Kanji characters suggest that early processing stages can be distinguish between regular and irregular Kanji forms [1, 2]. Thus, conventional ocular analysis can be effectively applied to single character strings. Recently, eye-tracking analysis of the reading process has even extended to clinical applications, such as providing diagnostic metrics for dyslexia or dementia [28].

Such observation may detect changes in cognitive process that causes mental workload during reading-aloud and character-perception tasks. Among ocular metrics, microsaccade (MS) - associated with high-level processing - and pupillary response - as established workload metrics - may represent workload levels and serve as indices for chronological assessment during oral reading. The feasibility of evaluating workload through MS activity and pupillary change warrants further examination using existing datasets [26].

This paper addresses these topics by analysing an open dataset of ocular metrics, focusing on the following objectives:

1. Extract and evaluate the chronological changes of both MS and pupil size to assess temporal mental workload during the oral reading of character strings.
2. Compare the mental effort required to read different types and lengths of character strings, in accordance with the experimental settings of the original study.
3. Apply a modelling technique to extract overall workload levels and assess differences in temporal changes across conditions.

Finally, the results of these analyses are synthesised to provide a comprehensive discussion of cognitive dynamics during oral reading.

2 Related works

Reading behaviour, including the underlying cognitive process, has been extensively studied using eye-tracking techniques [27]. A primary focus of conventional research is the prediction of reading comprehension ability based on eye-movement patterns. Given that modern reading occurs across both printed materials and digital media, the impact of presentation format is also frequently discussed [5]. Prediction accuracy is this field has improved significantly with the application of modern machine learning techniques [3]. Furthermore, analysis is no longer limited to general text reading; it now incorporates specific word properties and individual reading factors [33]. Developmental changes in reading behaviour are also a key area of study, particularly concerning children and second-language learners [29]. These eye-tracking advancements have been effectively applied to the detection of reading disabilities in both adults and children [7, 11].

While reading behaviour is traditionally studied in the context of silent reading, "reading aloud" provides a more observable measure of cognitive engagement. Research indicates that cognitive processes and viewing behaviours differ significantly between silent and oral reading [30]. Reading aloud reflects complex cognitive activities, such as memory performance [6], whereas overall reading performance often depends on presented visual factors [23]. Central to this relationship is the “eye-voice span” (EVS) - a metric that captures how the eyes search for and preview upcoming words before they are spoken. The EVS serves as a vital bridge between cognitive processing and eye movement [19, 34]. These insights have clinical utility, particularly in detecting diseases that affect cognitive workload, such as dementia [32, 16].

Considering these factors, word lengths and readability likely influence both oral reading performance and eye movements, even at the level of a single term. Previous studies have explored this by conducting reading experiments focused on these variables [9]. The key to evaluating these tasks lies in estimating the cognitive workload during the oral reading process. Recent research suggests that workload during such tasks can be effectively estimated using ocular metrics, specifically MS activity and pupil responses [18, 21]. In particular, MS consists of monocular and binocular components. The binocular components may reflect human high-level cognitive activity [25]. A post-processing tool to extract binocular components has been developed [31].

3 Method

Ocular metrics were recorded while participants read aloud strings consisting of numerals or alphabets. The visual stimuli comprised four character sets and two length conditions (Short and Long), resulting in eight distinct experimental conditions [9]. This study utilised the open dataset from these experiments for subsequent analysis [26].

1. Char1: Numerals without separators (Short and Long)
2. Char2: Numerals with separators (“”’’) (Short and Long)
3. Char3: French words (Short and Long)
4. Char4: Pseudowords (Short and Long)

Detailed experimental parameters are documented in previous studies [9, 26]. The “Short” condition consisted of 4 - 5 characters (including separators), while the “Long” condition presented 8 - 14 characters. Each of the four character types (Char1∼Char4) included 24 stimuli. The experiment was organised into two blocks, each containing 48 trials, with the block order randomly assigned to ensure counterbalancing. Participants were seated individually using chin and forehead rests at a distance of 930 mm from a 24-inch LCD monitor (60Hz). They were instructed to read the stimuli aloud as quickly as possible upon their appearance at the centre of the screen. Following each response, a black screen was presented for 100 ms before the next trial. Most tasks were completed within approximately 3 seconds for words and 5 seconds for numerals. Participants were 36 students (mean age=21.3), and their native language was French [9].

Monocular eye movements were tracked using an EyeLink1000 at 1 KHz. The raw dataset, including periods of missing data such as eye blinks, was obtained from the published source [26]. Missing data points were replaced using the last valid observation as a simple method to maintain time-series continuity and

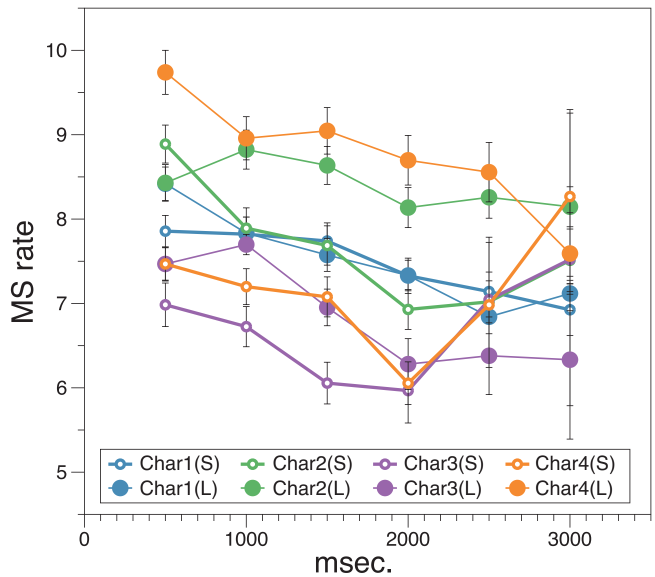

Fig. 1. Temporal changes of MS rate in eight conditions (error bars indicate std error)

minimise artefacts. While the original study focused on fixation and saccade metrics [9], the present work extracted temporal changes in MS rates and pupil sizes at 500 ms intervals to evaluate chronological workload.

As a primary metric of mental workload, MS events were detected from the recordings using the MS toolbox with default parameters [12]. Although MS events consists of both monocular and binocular components, this analysis focuses on the binocular components, as they are more robust indices of workload [25]. The procedure for isolating binocular MS components from monocular observations utilising an established methodology, specially binary classification based on patterns of ocular features within MS components [31]. These extracted binocular components were subsequently used for all analyses.

4 Results

4.1 MS rate

Focused binocular components were initially extracted from each individual observation set using the MS toolbox [12] and the binocular detection tool [31], a procedure designed to evaluate cognitive load. The resulting extraction rate for these components ranged from 0.51 to 0.99. This variance is likely due to interactions between experimental tasks and individual factors, with the latter appearing to be the primary influence. Because stimulus sequences were randomised during the experiment, specific external determinants for this range

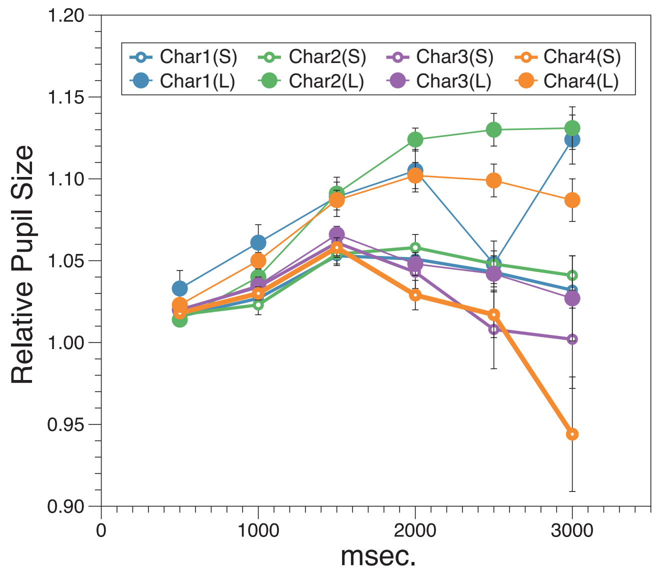

Fig. 2. Temporal changes of relative pupil size in eight conditions (error bars indicate std error)

could not be identified. The mean binocular extraction rate was 79%. The remained MSs consisted of monocular components.

The binocular MS rate (frequency of MS) was calculated for each 500 ms interval to observe chronological changes. These changes across experimental conditions are summarised in Figure 1, where the horizontal axis represents time elapsed since stimulus onset and the vertical axis indicates the MS rate per second. Data are plotted up to 3.0 seconds, as most trials were completed within this timeframe. Some irregular deviations appear toward the end of the interval as the number of active samples gradually decreased.

The overall trend indicates a decrease in MS rates following stimulus onset. The effects of experimental factors - specifically character type and string length - were examined using a two-way ANOVA at each time interval. The results indicate that string length (Short vs. Long) had a significant effect ($p < 0.05$) throughout the entire 3.0 - second duration. In contrast, the character type factor (Char1$\sim$Char4) reached significant ($p < 0.01$) only at 1500 ms mark. Notably, the interaction between these two factors was significant ($p < 0.01$) across the entire observed range.

4.2 Pupillary change

Because absolute pupil size varies significantly between individuals, the data were standardised to the baseline at stimulus onset (time=0s) for every trial; this is referred to as the relative pupil size. The temporal changes in pupillary response are summarised in Figure 2, following the same format as Figure 1, with the vertical axis representing the relative pupil size.

The response patterns exhibit two distinct trends: a monotonic increase for the Long condition (excluding Char3) and a peak at 1500 ms for the remaining conditions. These differing patterns suggest that the nature of the cognitive workload may vary between stimulus conditions. To compare these responses, a two-way ANOVA was also conducted. The results indicate that the factor of length (Short vs. Long) was significant ($p < 0.01$) across all character types, except at the 500 ms interval. In contract, the character type factor (Char1∼Char4) was not significant at any time point. The interaction between length and character type reached significance only at 2000 ms mark. Despite the visible differences in the trends of pupillary change, character type did not emerge as a statistically significant independent factor.

4.3 Relationship between MS rate and Pupil size

Internal stimulus factors, such as the presence of separators in numerals or wording types, generally did not reach statistical significance. However, for the MS rate, the wording factor (Words vs. Pseudowords) was significant ($p < 0.05$) between 1500 and 2500 ms. This delayed reaction may be attributed to the increased processing time required for longer stimuli. While an interaction between length and character type was observed during the numeral presentation, internal factors did not significantly affect pupil size, with the exception of the wording condition at 2000 ms. For both metrics, stimulus length remained the primary factor influenced the responses. As noted in the original study [9], ocular movements were generally suppressed during the tasks. Under these conditions, the decreasing MS rate may reflect a reduction in task difficulty or a shift in focus up to 2000 ms, whereas pupil size increases monotonically until reaching peak at 1500 or 2000 ms. The original study reported that the number of ordinal saccades increased in numeral conditions, but decreased when separators were presented. These variations in MS frequency likely explain the lack of significant differences in MS rates for numerals, as the ocular motor system may prioritise different types of saccadic activity depending on the stimulus structure.

Finally, certain artefacts influenced the temporal changes in both MS and pupil size, suggesting that more robust compensation procedures are required in future analysis. Furthermore, given the brevity of the tasks, shorter assessment windows may be necessary to capture these cognitive fluctuations more smoothly, these methodological refinements remain subjects for further study.

5 Estimation of Latent Activity

In this paper, workload fluctuations during oral reading are evaluated using both MS rates and pupillary changes. While the previous section compared these metrics chronologically, their underlying characteristics are not perfectly synchronised. To address this, the latent activity representing the internal state of the reader - is estimated using a state-space modelling technique [10, 22].

5.1 Modelling to Estimate Attention Levels

The estimation model is designed using a state-space framework [20, 15]. To ensure data consistency across all trials, the observation period was standardised to 5000 ms. For shorter trials, the final observed metrics were padded with the last valid observation until the 5000 ms mark. This padding was necessary to maintain a fixed data length and ensure balanced weight in the model. In this model, the attention level ($Attn$) is defined as the inverse of the sum of a latent activity level (S_level) - comprised of ten discrete states - and an individual parameter (rID), as shown in Equation (1). The latent activity term is intended to capture the various interacting factors that influence physiological responses during the experiment. State transitions are represented using Gaussian distribution, as shown in Equation (2). For the observation model, we hypothesise that changes in MS rates follow a Poisson distribution, given the nature of event frequency [24], Conversely, pupillary changes are modelled using a Normal distribution centred around the mean [10, 22]. While pupillary responses often show an inverse relationship with MS rates regarding attention levels [10], the observed pupillary metrics were used directly here, as this configuration resulted in the most stable model convergence.

$$Attn = inv\_logit(S\_level + rID) \tag{1}$$

State Model:

$$S\_level_i \sim Normal(S\_level_{i-1}, \sigma_s) \tag{2}$$

Observation Model:

$$\begin{aligned} mu_{noise} &\sim Normal(Attn, \sigma_{noise}) \\ \lambda &= exp(\mu_{noise}) \\ MS_{times} &\sim Poisson(\lambda) \\ Pupil_{size} &\sim Normal(Attn, \sigma_p) \end{aligned}$$

All model parameters were estimated using the extracted observation data and Markov Chain Monte Carlo (MCMC) sampling. We performed 4000 iterations across four chains with a 1000-iterations burn-in). Model convergence was confirmed by an $\hat{R}value < 1.1$ using R and Stan packages. Although the individual parameters (rID) varied across participants, these differences are not discussed in detail here due to the large sample size.

5.2 Estimated Internal Activities

The attentional levels estimated by the model - represented as mean values for every condition across time - are illustrated in Figure 3. The horizontal axis represents the extended time course of 5000 ms, while the vertical axis indicates the estimated level of attention, reflecting the degree of cognitive workload. As shown in the figure, attention levels across all conditions remain

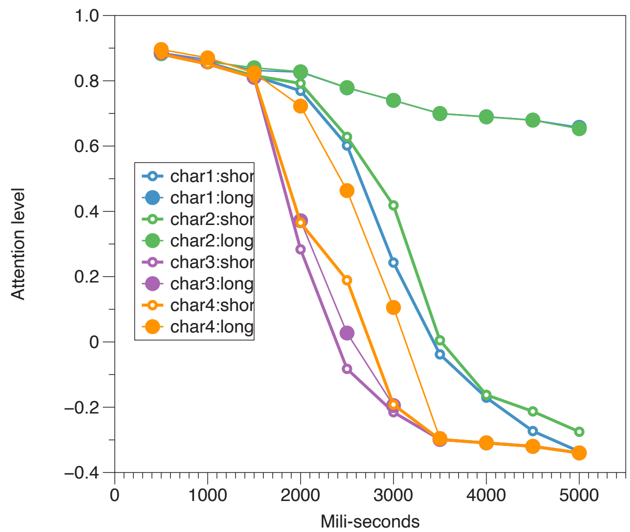

Fig. 3. Temporal changes of "Attention level"

nearly identical between 500 and 1500 ms. However, distinct patterns emerge thereafter. For Char3 (words) and Char4-short (short pseudowords), attention levels drop sharply after 1500 ms. A second group - comprised of Char4-long and the short conditions of Char1 and Char2 - exhibits a more gradual decrease, with Char4-long specially dropping off around 3500 ms. Finally, the long conditions for Char1 and Char2 (numerals) overlap significantly, maintaining high attention levels throughout the observation period.

These variations likely represent the perception processes involved in reading the stimuli aloud. For instance, Char3 (standard French words) may be recognised quickly, with tasks completed by 2000∼3000 ms. In contrast, the second group (Char4-long and short numerals) likely requires character-by-character processing, resulting in a prolonged but eventually declining level of attention. Long numerical strings, which require the serial processing of every character, demand a high level of attention until the trial's conclusion.

The estimated attention level incorporates individual factor (rID). To isolate the task-driven component, the chronological latent activity (S_level) are illustrated in Figure 4. The trends here can again be classified into three groups:

– Linguistic Stimuli (Char3 & Char4): In the Char4 condition, levels decrease until 2000∼3000 ms. For standard words (Char3), the length of the word directly affects the level, with processing concluding quickly. The "flattening" of these levels suggests the end of the cognitive task.
– Short Numerical Stimuli: Short conditions for Char1, Char2, and Char3 maintain a relatively stable level until 3500 ms.

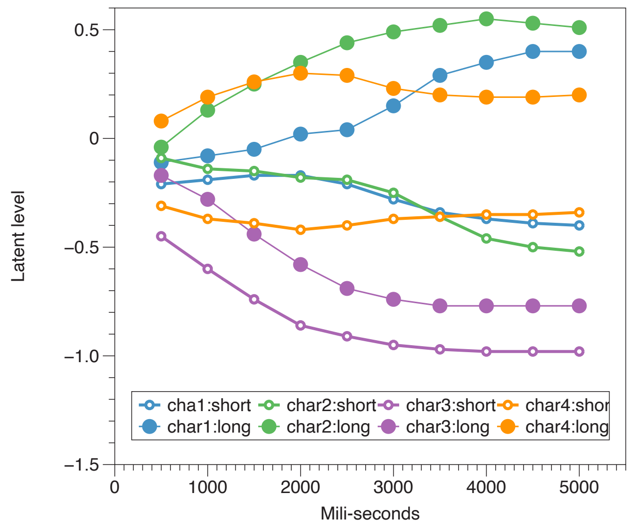

Fig. 4. Temporal changes of "latent activity level"

– High-Complexity Stimuli (Long Numerals): The remaining long conditions exhibit a baseline and a gradual increase in activity until 2000∼4000 ms, suggesting that task difficulty significantly influences these levels. Notably, Char2-long(long numerals with separators) shows higher activity than Char1-long(without separators). This suggests that for long strings, separators may act as a distractor or increase the coordination load, whereas they have little impact on short strings.

These results and discussions were based on a hypothesised model which consisted of both ocular metrics driven by the chronological change of the latent activity level. The model solution was extracted as a convergence of all parameters using the observed metrics. Furtermore, the validity of modelling and data processing should be examined carefully. Moreover, as these transforms are not significantly supported by any bio-mechanisms, a major response may represent a unified measure of MS rate and pupillary change. The assessment of the results requires attention to these points; however, it may serve as an index to represent the trends of both changes, rather than assessing metric changes independently.

6 Summary and Conclusion

This study evaluated cognitive workload during the oral reading of character strings using microsaccade (MS) rates and pupillary changes. The stimuli consisted of four format types across two length conditions (short and long): numeral strings with and without separators, standard French words, and

pseudowords. All data analyses and model estimations were conducted using an open dataset [26].
The findings are summarised as follows:

1. Metric Extraction: To assess mental workload during oral reading, both MS rates and pupil sizes were extracted chronologically until task completion. MS rates were calculated using binocular components identified via a specialised detection system. The mean binocular MS extraction rate was 79%.
2. Comparative Analysis: We compared MS rates and relative pupil sizes across stimulus types and lengths. Both metrics revealed significant deviations over the time course of the task. Notably, string length was a significant factor across both metrics, whereas character type contributed to significant differences only under a few limited conditions.
3. Latent Activity Estimation: A state-space modelling technique was employed to estimate the reader's latent attentional activity by integrating all observed ocular metrics. the resulting attention levels were categorised into three distinct response groups:
   – Standard French Words: The estimated workload dropped off rapidly, suggesting efficient recognition and processing.
   – Short Strings: Workload levels remained relatively stable throughout the task.
   – Long Strings: In contrast to the other groups, workload increased steadily from stimulus onset until the conclusion of the task.

These results suggest that conventional eye-tracking metrics may not always fully capture the nuances of cognitive workload in isolation. Instead, analysis must account for the specific cognitive processes required for oral reading. The interaction between ocular metrics and the "speech act" - specifically how different character sets influence vocalisation timing and phonetic decoding - remains a compelling subject for future investigation. Future research should therefore focus on developing an application procedure to evaluate reading activity, thereby providing a diagnostic tool for conditions such as dementia or reading difficulty.

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