Preliminary Eye Tracking Scale for Cognitive Load

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Abstract

The article examines the role of technology in social campaigns and cognitive overload in advertising. It critiques traditional cognitive load measurement methods and suggests using eye tracking for more accurate assessments. The authors recommend a cognitive load assessment scale that considers differences between static and dynamic presentations and eye tracking correlations. Differences in correlations based on stimuli type led to identifying a condensed set of measures for videos and images. These findings refine eye-tracking methodologies and enhance cognitive load assessment tools, positioning eye tracking as a reliable method for measuring cognitive load in advertising and improving communication strategies in social campaigns.

Keywords: digital communication, eye tracking, cognitive overload, scale development, media channels.

1. Introduction

In today's dynamic world, technology plays a crucial role in almost every aspect of life, revolutionizing the way we communicate, acquire information, and organize society [48, 54]. The introduction of information technologies for social good reflects not only the growing recognition of technological potential but also the need to harness it to address real social issues. It is precisely technology that enables the creation of social campaigns and their promotion through various forms of media [32]. Utilizing technological communication platforms, such as the internet, social media, or mobile applications, enables broad-reaching engagement with audiences to build awareness and enhance understanding of significant social issues [4]. However, changing attitudes and behaviors through campaigns (regardless of the technologies used) is difficult, because people are sometimes reluctant to adopt the message that is presented to them due to the cognitive dissonance [38] or reactance [9]. Therefore, to make the change possible, social campaigns and advertisements must be properly constructed.

According to the Limited Capacity Model of Motivated Mediated Message Processing (LC4MP), people have limited cognitive resources for information processing [44]. Also, the Cognitive Load Theory [56] assumes that the human brain has limited capacity. High message volume leads to inefficiency in processing and difficulties in understanding and assimilating information. The inflow of information can reach an intensity beyond which the recipient's typical cognitive abilities are impaired [20]. To better assimilate messages, it is necessary to reduce the amount of information. Social campaigns can cause cognitive overload with excessive information [34]. Additionally many factors can contribute to cognitive overload in social advertising including message editing techniques [55], emotional information [11], argument strength [24], message format [19] and structure [25]. Evaluating media messages in terms of cognitive load and recipient expectations is crucial for improving their effectiveness.

The literature presents various traditional methods for measuring cognitive overload, including surveys, questionnaires, and qualitative interviews [5, 43]. The main disadvantage of such measurement is that cognitive overload ratings are self-report measures [29] and are highly subjective because they are based on respondents' declarations. The results depend on the consciousness of the respondents. The collected data often do not represent the real state of the respondents' cognitive resources, and therefore are burdened with considerable measurement errors [13]. A lot of previous experiments studying cognitive overload and advertising effectiveness have used neurophysiological techniques to measure consumers' unconscious responses [13]. In the conducted experiments to study cognitive overload, authors mainly apply three neurophysiological methods to collect data: eye movements (eye tracking), heart rate variability (HRV) and brain responses (EEG) [5]. Very popular is eye tracking (ET) since it is estimated that over 80% of the information people acquire is acquired through visual channels [49]. In studies involving eye tracking, there is a wide range of different measures utilized by various authors and in different experimental configurations [63]. The main eye indicators used to assess cognitive load include saccades and fixations [8], pupil size and movement [33], [37], and blink analysis [5], [63]. Fixation is the moment when the eye remains focused on a single point in the field of view, allowing for detailed analysis, while saccades are rapid eye movements used to shift the gaze from one point to another [5, 36]. These measures also encompass advanced indicators, such as micro-eye movement indices and eye scanning patterns [31]. It has been demonstrated that blink frequency and duration decrease when participants are exposed to high visual load [7]. In turn, pupil diameter generally increases with higher levels of cognitive processing as a result of central autonomic nervous system activity [57] and is sensitive to rapid changes in cognitive load [6]. However, due to the measurement specifications and physiological interdependence among different ET parameters, many of these measures are strongly correlated [58]. This means that they essentially measure the same feature, which limits their informational value. For example, the number of saccades and fixation duration may be highly correlated, as longer fixations typically lead to a greater number of saccades [60]. Consequently, using both measures simultaneously may be redundant. Additionally, when assessing cognitive load using eye tracking, it is essential to consider specific contexts of visual presentation, such as differences between static images and dynamic videos [47]. The results of numerous studies confirm that eye movements significantly differ in these two cases, which can impact the interpretation of eye-tracking results [17]. Eye movement parameters may also be influenced by repeated presentation of stimuli, image type, the interestingness of the images, and individual motivational dispositions [27]. Authors emphasize the need to account for these differences and adjust the research methodology depending on the specificity of the presented content. This will allow for a more accurate assessment of cognitive load in various visual contexts and a better understanding of eye reactions to diverse stimuli.

The article explores the relationship between cognitive load and eye tracking measures, aiming to develop a scale for assessing cognitive load using eye tracking technology. This scale will consider differences between static images and dynamic videos, as well as various eye tracking measures used by different authors. Standardizing measurement procedures will enable more efficient assessment of cognitive load in different research contexts. Additionally, leveraging technological methods like eye tracking could enhance social campaigns and advertising effectiveness by understanding cognitive load induced by campaign materials, ultimately leading to positive societal changes.

2. Research framework

We propose a framework to develop and validate a scale for eye-tracking cognitive workload assessment, as shown in Figure 1. This systematic approach ensures the scale's reliability and validity, enhancing its real-world applicability.

Initially, a literature review is essential to inform further research design and identify the most relevant measures [12]. Subsequently, the most popular measures are selected to ensure that the proposed scale builds on established, validated metrics [16]. The next step involves designing an experiment focused on a specific social campaign topic as planned experiments are critical for ensuring the reliability of the measures used [52]. The selection of stimuli is crucial, as engaging and contextually appropriate stimuli ensure participants remain attentive and provide authentic responses, leading to more reliable data [59].

<table>
<tr><td colspan="2">Literature review to identify the commonly used measures</td></tr>
<tr><td colspan="2">Selection of the most popular measures</td></tr>
<tr><td rowspan="2">Preparation of the experiment to check the chosen measures and correlations between them</td><td>Choice of the social campaigns’ theme</td></tr>
<tr><td>Selection of stimuli</td></tr>
<tr><td colspan="2">Experiment execution and data collection</td></tr>
<tr><td colspan="2">Data analysis</td></tr>
<tr><td colspan="2">Selection of the recommended measures set</td></tr>
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Fig. 1. Research framework.

This experiment explores the correlations between various objective eye-tracking measures cognitive load ratings. Data gathered will go through statistical and qualitative analysis to evaluate the measures' effectiveness [12]. Correlational analysis will be used to examine the relationship between objective cognitive load measures [16]. Next, the most representative eye-tracking measures will be selected. This step aligns with the principles of scale development, where iterative testing and refinement are essential [22]. The scale's utility and reliability must then be confirmed through further experiments conducted under varied conditions and with diverse audiovisual content. This step is akin to the validation processes recommended by Nunnally and Bernstein [40], which stress the importance of multiple validation studies to confirm a scale’s reliability and validity. Based on these findings, the tool will be refined, enhancing the scale to improve measurement accuracy and its applicability in analyzing social campaign materials.

3. Experimental case study

3.1. Literature review

Based on conducted literature review we have identified the eye-tracking measures that are commonly used in the context of cognitive load. These are fixations, blinks, saccades and pupils. Fixations are characterized by their duration [2, 3, 15, 18, 26, 28, 50, 62], number [1, 18, 21, 28], frequency [3, 15, 26, 39]. Blinks are measured by frequency [3, 10, 26, 50], duration [3, 10, 23, 50], number [18, 23]. Saccades are evaluated mostly by magnitude [23, 30], frequency [1, 3, 26, 30], amplitude [2, 3, 15, 50] duration [15, 26, 50] velocity [3, 23, 28, 50] latency [3], length [28], number in different AOIs [18] and pupils by the diameter [1, 2, 23, 26, 39, 61, 63].

3.2. Selection of the most popular measures

For the further steps, we will focus on measures including saccades (frequency, amplitude, duration, velocity), fixations (duration, number, frequency), pupil diameter, and blinks (frequency, duration, number).

3.3. Preparation of the experiment

Topic of the social campaign

Taking into account the growing importance of communication technologies such as mobile phones, and the associated risks to road safety [42], publicly available social advertisements promoting safe driving were used for the study. These advertisements were used in campaigns aired in Poland to ensure all participants understood them. Using foreign languages could have added cognitive load, impacting the experiment's results.

Selection of stimuli

The experiment utilized 5 still images (static stimuli) and 4 videos (dynamic stimuli) to examine how modality affects cognitive load. The selected advertisements addressed the same campaign objective, which is to reduce the number of accidents caused by using a phone while driving. All materials were displayed for a similar duration (around 30 seconds) to facilitate better comparison between them. Both the stimuli within each category and the categories were presented in random order to avoid the situation where the last stimulus is consistently rated as the most cognitively demanding.

3.4. Execution of the experiment

Participants

A total of 33 students (25 males) participated in the study. The sample size meets cognitive neuroscience standards of 30 participants per group for significant results [45] and is suitable for a preliminary study. Participants were selected based on availability and willingness. The mean age was 23 years, with a standard deviation of 0.72. Most participants (31) were right-handed. The study included licensed drivers (94%) and non-drivers. Since cognitive load occurs regardless of driving experience, assessing both groups provides a comprehensive understanding of these social initiatives' impact.

Procedure

The study, approved by the Bioethics Committee of the Regional Medical Chamber, lasted 30 minutes per participant, including equipment setup. Participants signed a consent form after being informed about the study. The first stage of the study involved presenting stimuli while collecting psychophysiological data in real time. At the beginning, a relaxation slide was presented to calm the participants. Subsequently, stimuli within a single group were presented in a random order. A relaxation break was provided between the different stimulus groups to reduce cognitive overload before the next message. The second stage of the study involved completing a survey to gather demographic data, in which participants declared for what purpose they use their phones while driving.

Data collection and processing

Eye movements were measured using a Tobii Pro X3-120 eye tracker at 120 Hz [14], mounted on a 15-inch Full HD monitor displaying stimuli and questionnaires. The iMotions software allowed the immediate generation of data visualizations in the form of heatmaps and areas of interest [46].

4. Results

Prior to statistical testing, eye tracker data were normalized using Z-scores based on baseline activity (relaxation), enabling comparison of cognitive load between stimulus groups across all participants. Normality of eye tracking data distribution was assessed using the Shapiro-Wilk test, revealing that 53 out of 121 data series (43.8%) were normally distributed. Consequently, non-parametric tests were utilized for the remaining statistical analyses involving eye tracking.

The experiment aimed to gather various eye tracking measures for assessing cognitive load and propose an optimal set of metrics. Spearman's correlation was calculated between each pair of measures to identify strong correlations, such as fixation frequency and saccade frequency, blinks number and blinks frequency, and saccade duration and saccade velocity, influenced by ocular physiology. Eye movements also varied between videos and images due to the presence or absence of movement [35].

Dynamic differences in visual stimuli, such as images and videos, significantly influence eye movements, including saccade and fixation parameters, due to varying eye globe movements over time [53]. It is crucial to analyze correlations separately for each type of presentation to uncover differences or similarities. This approach could lead to separate assessment scales for images and videos or a combined scale that integrates their unique characteristics.

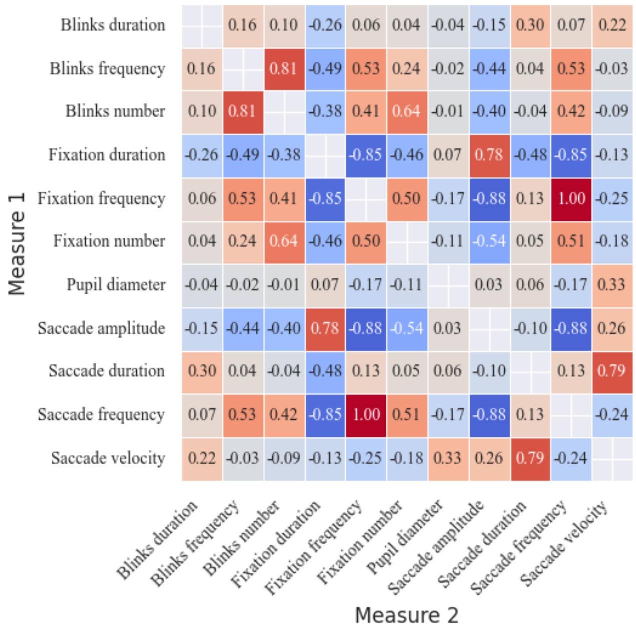

Fig. 2. Spearman's rank correlation coefficient between eye tracking measures for video clips.

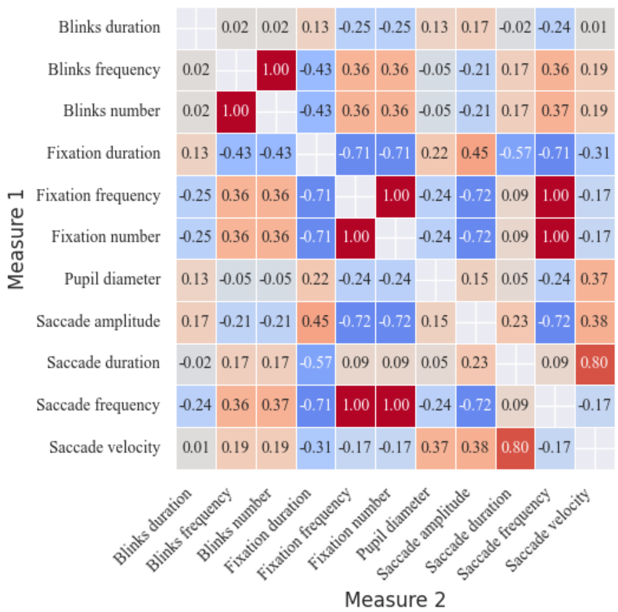

Fig. 3. *Spearman's rank correlation coefficient between eye tracking measures for images.*

Spearman's correlation coefficients between eye tracking measures for videos and images (Figures 2 and 3) show significant variations depending on the stimulus type. This suggests the need for distinct scales tailored to different stimuli. Based on the obtained correlations, we aimed to reduce the set of measures to avoid the redundancy. To achieve this goal, we have set the threshold that indicates the strong relationship between the variables. Following some recommendations that can be found in the literature, we have assumed that in our case this threshold will be set to 0.7 [51]. First, the highly correlated pairs of measures were identified and then one element of each pair was removed – it was always the one that had a higher average correlation with all other features. Applying this procedure to the obtained correlation matrices, we have determined the reduced set of measures for video clips and images. The results are presented in the Table 1.

The sets determined based on high average correlation between the measures both for videos and images are similar. Apart of the fixation, other metrics connected with blinks, saccades and pupil diameter seem to be appropriate in the context of investigating the cognitive load irrespectively of the stimuli type. We have compared obtained results with the sets of measures that were applied in the literature. The exact set of measures that was proposed based on our results was not used in any of the cases. For dynamic stimuli the most of the chosen metrics were used in case of the research conducted by Johannessen et al. [26] and for the static stimuli in the research of Behroozi et al. [3].

Table 1. Reduced set of eye-tracking measures depending on the type of the stimuli.

Type of stimuli	Measures
Video	Blinks duration, Blinks frequency, **Fixation number**, Pupil diameter, Saccade amplitude, Saccade duration
Image	Blinks duration, Blinks frequency, **Fixation duration**, Pupil diameter, Saccade amplitude, Saccade duration

The simplified set of proposed measures, although is not exactly applied in analogous research, shows similarities to metrics used in various dynamic and static contexts, confirming the validity of our approach. These results not only contribute to the optimization of eye tracking methodologies, but also provide directions for future research to further validate and improve cognitive load assessment tools in a variety of applications.

5. Discussion and conclusions

Our study developed an assessment scale linking eye tracking to cognitive load, adapting to differences in static and dynamic presentations and correlations among measures. Despite varying correlations based on stimulus type, indicators like blinks, saccades, pupil diameter, and fixation reliably assessed cognitive load, reinforcing our approach's validity alongside broader usage in different contexts.

Our study enhances cognitive load assessment across diverse research settings and standardizing measurement procedures in eye tracking studies. Addressing concerns raised by Onwuegbusi, Hermens, and Hogue [41], we segment eye tracking data by stimulus type (images vs. videos) to improve accuracy. We found distinct impacts of dynamic and static stimuli on eye movement parameters, necessitating separate assessment scales. Strong correlations between measures like fixation frequency and saccade frequency, and blink count and blink frequency, guided us in reducing redundancy. Setting a correlation threshold of 0.7, based on literature, streamlined our selection of essential eye tracking measures for both stimulus types. Our research refines cognitive load assessment methodologies and proposes a streamlined measure set applicable across various research contexts, advancing tools for cognitive load assessment.

While our study offers a novel approach to cognitive load assessment via eye tracking, it has limitations to acknowledge. Firstly, our analysis included only images and videos, potentially restricting applicability to other media types. Secondly, participant diversity (e.g., age, gender, education) was limited, which may affect generalizability. Lastly, although we proposed a streamlined measure set for cognitive load research, further validation across diverse contexts and populations is necessary.

Future research should address these limitations by expanding the participant pool to be more diverse and inclusive. Moreover, incorporating various stimuli like texts, animations, video games, virtual reality, and augmented reality would offer a broader understanding of cognitive load effects. Exploring stimuli across different themes (e.g., educational, advertising, entertainment) could illuminate how content influences eye movements and cognitive load. Integrating eye-tracking with other measurement methods such as EEG, ECG, or galvanic skin response could provide a more holistic assessment of cognitive load.

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