Eye-tracking correlates of the Implicit Association Test

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***Abstract*— Raising awareness of environmental challenges represents an important issue for researchers and scientists. As public opinion remains ambiguous, implicit attitudes toward climate change must be investigated. A custom Single-Category Implicit Association Test, a version of the Implicit Association Test, was developed to assess climate change beliefs. It was administered to 20 subjects while eye movements were tracked using a smart glasses system. Eye gaze patterns were analysed to understand whether they could reflect implicit attitudes toward nature. Recurrence Quantification Analysis was performed to extract 13 features from the eye-tracking data, which were used to perform statistical analyses. Significant differences were found between target stimuli (words related to climate change) and bad attributes in reaction time, and between target stimuli and good attributes in diagonal length entropy, suggesting that eye-tracking may provide an alternative source of information to electroencephalography in modeling and predicting implicit attitudes.**

I. Introduction

In recent years, scientific efforts have increased to promote responsibility for the challenges climate change brought and to encourage environmentally friendly behaviours, but public opinion remains ambiguous and has not attracted the expected interest and commitment. Therefore, researchers have begun to examine education, ideologies, and psychological factors, such as attitudes toward nature, in order to define models and programs that can help raise awareness of these issues [1], [2].

Attitude can be defined as a favorable or unfavorable disposition toward social objects, such as people or norms [3]. Acquired knowledge blends with the variables we are exposed to (emotions, environment, etc.) and forms our attitudes [4], [5]. They can be split into explicit and implicit attitudes. Explicit attitudes can be measured using questionnaires whilst to access implicit ones, methods need to bypass conscious introspection and obtain relevant psychometric correlates that are not based on self-reports.

The Implicit Association Test (IAT) became one of the most common methods for assessing automatic concept-attribute associations underlying implicit biases, prejudices, and beliefs [6]. Many variants have been developed over the years: the Single Category IAT (SC-IAT) [7] was proposed to overcome the difficulty of defining a complementary category and to simplify the interpretation of IAT results. The SC-IAT, like the traditional IAT, has proven that decision-making reaction times are faster for congruent associations than for incongruent associations. The reason for this remains unclear, but two hypotheses can be made:

- The participant performs additional mental processes to inhibit their own automatic, stereotypical evaluations or beliefs.
- The participant performs the same mental processes, but they require more time to complete (e.g., selecting a motor response).

To account for the IAT effect, i.e. the difference in mean latency between congruent and incogruent associations [3], various papers have investigated electroencephalographic (EEG) signals processing techniques to understand mental processes and identify involved brain regions during IAT experiments. Specifically, they compared congruent and incongruent associations: for instance, in a nature-centred IAT, Healy et al. [8] found out that the N200 in left temporal lobe (where language is processed) and the P300 in medial frontal gyrus (associated with go/no-go decisions [9]) present significant differences; moreover, both event-related potentials show significant differences in postcentral gyrus, the location of the primary somatosensory cortex.

IAT is based on visual stimuli (usually words or pictures), thus eye gaze patterns were analysed to measure how subjects interact and scan observed scenes and understand whether they play a role in delaying responses. Several researches have succesfully used eye-tracking metrics to study cognitive load, attention and emotion [10]. Characterisation of eye movements can be performed using linear methods (e.g., by examining the frequency spectrum) or nonlinear techinques. Recurrence Quantification Analysis (RQA) is defined as a nonlinear data analysis strategy that quantifies the number and duration of recurrences of a dynamical system presented by its state space trajectory: this method was proposed by Zbilut and Webber [11] to quantify the structures of recurrence plots. It has been used in many contexts and Anderson et al. [12] proved that RQA represents a powerful tool for discovering and characterising fixation sequences and repeated scan paths. To the authors' knowledge, this is the first work describing the temporal dynamics of eye movements during an IAT experiment.

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The scope of this study is to understand whether the underlying causes of the IAT effect determine changes in RQA parameters between congruent and incongruent associations and if they can detect alterations between stimulus categories.

II. Materials and Methods

Tobii Pro ® Glasses 3 (Tobii Pro AB, Danderyd, Sweden) was used to acquire the gaze signal. The sampling rate was 50Hz. An optical sensor-based triggering system was used to track words transitions.

Twenty-four healthy volunteers (6 males, mean age = 24±3) were recruited. Explicit climate change attitudes were assessed with the Beliefs about Global Climate Change (BAGCC) scale [13]. Four subjects were excluded due to glasses that prevented them from wearing the eye-tracking system. This study was approved by the Institutional Review Board and all participants gave written informed consent.

A. Implicit Association Test

A two-stage SC-IAT was developed to examine the degree of connectedness with nature in each individual. The associations are based on 24 words divided into three categories: target (words related to climate changes), credible words, and dubious words (see Table I). Participants were seated in front of a computer monitor and a keyboard: in the first phase, they had to press the key "Z" for credible and target words and "M" in case of dubious words (congruent association) as fast as possible and without time limit; in the second phase, they had to press "Z" for credible words and "M" for target and dubious words (incongruent association). Each phase is in turn separated into a practice section, made of 24 trials, and a test part with 72 trials. Stimuli are randomised and balanced in each section; they are presented by a custom web-based application. After each decision, the interface displays the following word after 1500ms.

TABLE I
SC-IAT stimuli categorisation

WORDS		
TARGET	**CREDIBLE**	**DUBIOUS**
Global warming	True	Wrong
Greenhouse effect	Verified	False
Ozone depletion	Certain	Erroneous
CO2 emissions	Real	Incorrect
Sea level rise	Proved	Unfounded
Climate change	Valid	Discredited
Ice melting	Evident	Unlikely
Air pollution	Tested	Irrational

B. Eye-tracking Analysis

For each subject, the entire eye-tracking matrix was decomposed in x and y coordinates and preprocessed to remove artifacts (e.g., calibration loss due to sudden head movements) and blinks: after thresholding, a shape-preserving piecewise cubic interpolation is performed and then a moving average filter is applied to remove possible outliers. Fig. 1 shows an example of filtered signal: the top panel displays the raw gaze signal, the middle panel illustrates the three preprocessing steps and the bottom panel shows the filtered one.

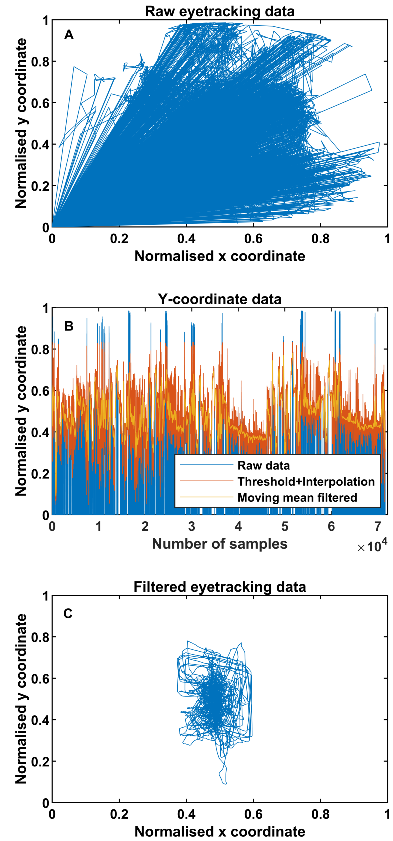

Fig. 1. Preprocessing of raw eye-tracking data. A) Raw gaze signal. B) Three steps procedure to filter coordinate data. C) Filtered gaze signal.

The filtered gaze signal is converted into a monodimensional vector by calculating the Point-to-Point Instantaneous Gaze Direction (PPIGD) to facilitate the description of its nonlinear dynamics [14]; it is computed considering the arctangent of the spacial segment for each pair of successive gaze points whose coordinates are $g_i = (g_{x,i}, g_{y,i})$. Specifically, considering two consecutive gaze points referred to the horizontal ($\Delta g_{x,i}$) and vertical ($\Delta g_{y,i}$) decomposition we can define:

$$\theta_i(tq) = \arctan \frac{\Delta g_{x,i}(t)}{\Delta g_{y,i}(t)} \tag{1}$$

Trigger signal was used to automatically segment PPIGD vectors into single-word length intervals. Phase space reconstruction was performed according to Takens's theorem, implementing a time delay embedding algorithm [15]. A MATLAB ® 2020b code (The Mathworks Inc., Natick, Massachussetts, USA) was developed to iteratively select for each interval the embedding dimension m as the first minimum of the false nearest neighbours function and the time delay τ as the first minimum of the mutual information profile. RQA allows the quantification of the dynamic properties of a system represented in phase space and is based on the Recurrence Plot (RP). The threshold ε was chosen as the maximal phase space diameter, considering m and τ. The CRP toolbox [16] was used to extract 13 RQA features from the RP: Recurrence Rate (RR), Determinism (D), Average Diagonal Length (ADL), Longest Length of Diagonal Lines (LLVL), Entropy of the Diagonal Length (EDL), Laminarity (L), Trapping Time (TT), Longest Length of Vertical Line (LLVL), Recurrence Time of 1° Type (RT1T), Recurrence Time of 2° Type (RT2T), Recurrence Period Density Entropy (RPDE), Clustering Coefficient (CC) and Transitivity (T). Reaction Times (RT), i.e. the time interval between stimulus presentation and decision, were extracted considering the trigger signal. To understand whether subjects' responses to the stimuli varied between congruent and incogruent associations, we computed the difference between identical words (e.g., the first "ice melting" in the first test section and the first "ice melting" in the second); we then normalised the features using the min-max algorithm. Statistical analysis was performed to determine whether physiological (RQA) and behavioural (RT) features presented significant differences between word categories: a one-way ANOVA test with an α-level of significance = 0.05 and a post-hoc analysis with Tukey correction were performed. Furthermore, bivariate Pearson correlation analysis was implemented to identify relationships between RT and RQA parameters on a global scale, i.e., without subdividing words into categories.

III. Results

Table II summarises ANOVA results: statistically significant differences between word categories were found for EDL, L and RT. Post-hoc analysis highlighted a difference for EDL between target and credible words (p-value = 0.0266), for L between credible and dubious words (p-value = 0.0347), for RT between target and dubious words (p-value = $5.82*10^{-4}$). Fig. 2 displays the boxplots for EDL, L and RT across Target, Credible and Dubious words.

Some weak correlations were found for LLDL (ρ = 0.1101, p-value = $3.44*10^{-5}$), LLVL (ρ = 0.0995, p-value = $1.87*10^{-4}$), RT1T (ρ = 0.2447, p-value = $1.618*10^{-20}$), RT2T (ρ = 0.2969, p-value = $4.53*10^{-30}$).

IV. Discussions

It is well known that incongruent associations in the IAT cause slower reaction times. Specifically to this work, RT is significantly lower for target words than dubious words. This may be related to the negativity bias, a widespread psychological principle according to which the negative, in this experiment represented by incogruent associations, is more causally efficacious than the positive [17]. This result could be expected due to the high scores achieved in the BAGCC scale, which reflect stronger beliefs in climate change.

Such phenomenon could also be explained by eye gaze characterisation with RQA metrics. EDL is related to the Shannon entropy of the distribution of diagonal lines in the RP, representing parallel segments of phase space trajectories [16]. It is computed as:

$$EDL = -\sum_{l=l_{min}} P_D(l) \ln P_D(l) \tag{2}$$

where $P_D(l)$ is the number of diagonal lines with length $l > l_{min}$.

EDL diminishes from target to credible words, suggesting that for target words more information are required to recover the system due to a more complex RP [18]. It also highlights a higher periodic behaviour between incongruent vs congruent associations for target words. This means that, while observing target words, eyes movements may experience regularly repeated gaze patterns. Moreover, post-hoc analysis showed that target and dubious words do not differ with each other (p-value = 0.870), which could mean that in section 2 subjects tend to scan more periodically the monitor due to increased attention as the pressing key for target words changes from section 1 and consequently influence dubious terms.

L is defined as the ratio between recurrence points forming vertical structures and the entire set of recurrence points: vertical lines symbolise phase space trajectories which remain in the same area of the phase space for some time. Its formula is expressed in Eq. 3.

$$L = 100 \frac{\sum_l l P_V(l) + \sum_l l P_H(l)}{2R} \tag{3}$$

where $P_V(l)$ and $P_H(l)$ are the number of vertical and horizontal lines with length $l > l_{min}$, and R is the number of recurrences in the RP.

In terms of eye movement, this parameter is sensitive when a subject quickly focuses on an area in a single fixation and later rescans the same area in detail [19]. The mean value of L for credible words is lower than dubious ones, indicating less stable phase space trajectories. Therefore subjects rapidly decide which key to press in case of credible words but more time seems to be required for dubious ones because they watch monitor area longer.

Correlation analysis showed that it is possible to use, as alternative measures to RT, RT1T and RT2T to carry out analyses with physiological features only. However, their low values suggest that RT and RQA metrics provide different information and they should be used concurrently. Recurrence times correspond to vertical distances between recurrence points in the RP and they can be associated with the average time eyes take to approximately travel along previously covered trajectories [20].

Eye movements can not identify which brain areas are activated during an IAT, however, since vision is controlled and modulated by the central nervous system, their analysis may reflect underlying mental processes: from our results, it seems that no additional operation is performed, but rather it is required more time for visual stimuli elaboration in response to their categorisation.

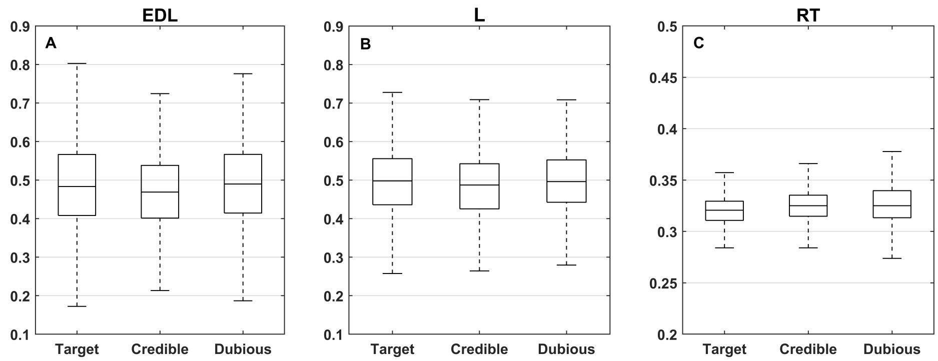

Fig. 2. A) Boxplots for EDL. B) Boxplots for L. C) Boxplots for RT (magnified to make distribution differences more evident).

TABLE II

ONE-WAY ANOVA RESULTS. EACH RQA PARAMETER WAS COMPARED BETWEEN THREE WORD CATEGORIES (TARGET, CREDIBLE, DUBIOUS).

RQA parameter	p-value	F-statistic	Mean±Std, Target	Mean±Std, Credible	Mean±Std, Dubious
EDL	0.0240	3.74	0.4948±0.1335	0.4737±0.1165	0.4906±0.1257
L	0.0209	3.88	0.5000±0.1252	0.4820±0.1134	0.5012±0.1160
RT	$9.55*10^{-4}$	6.99	0.3179±0.0538	0.3244±0.0336	0.3291±0.0482

V. CONCLUSIONS

The IAT is a powerful tool for investigating implicit attitudes toward various social and environmental issues. In this paper, we propose a promising strategy based on eye-tracking and RQA to help literature studies answer the IAT's open-ended questions. Longer reaction time in the incogruent association domain could be the consequence of longer neural processes, reflected in two RQA parameters, EDL and L, that present valid physiological explanations. To support these results, since this study is limited to eye-tracking, it will be important to analyse EEG signals acquired with the same experimental layout to identify inhibition operations or measure processing times in the brain. More participants must be included, also to ensure non gender biased outcome, and other nonlinear methods need to be explored and applied to eye-tracking data.

This could help predict subjects responses and thus their implicit attitudes toward climate change, raising awareness about these issues.

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