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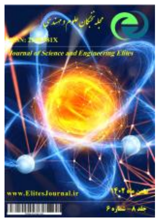
مجله نخبگان علوم و مهندسی

Journal of Science and Engineering Elites

جلد ۸- شماره ۶ - سال ۱۴۰۲



Review of Cognitive Neuroscience Revolution

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Received: January 2024 Accepted: February 2024

Abstract

Neuroscience, also known as Neural Science, is the study of how the nervous system develops, its structure, and what it does. Neuroscientists focus on the brain and its impact on behavior and cognitive functions. We first show how our eye-tracking setup has been optimized for recording high-quality eye-tracking data. Second, we show that eye-tracking data quality can be operator-dependent even after a thorough training protocol. Finally, we report distributions of eye-tracking data quality measures for four age groups (5 months, 10 months, 3 years, and 9 years). In other words, as children age the proportion of time that only one eye can be tracked is reduced and the amount of data loss that occurs at all. Verbal stimuli work better than pictorial stimuli. In the case of verbal stimuli, gender and level of neuroticism are found to be important variables that influence unconscious perceptual decision-making processes. Specifically, a female with a high level of neuroticism shows greater permeability in its unconscious perceptual processes. To test these processes, a set of ANOVA models and logistic regressions were run where the dependent variable is whether the people perceived the stimuli or not and the independent variables were gender, the form of the stimuli (pictorial or verbal), and the personality traits extroversion, introversion, and neuroticism. Neuroscience studies the effectiveness of social advertising in the context of promoting a healthy lifestyle. The respondents' reactions (emotions, remembering, and interest) to individual fragments of the advertisement are analyzed and we can see their direct effect on each other.

Key Words: Neuroscience, Nervous System, Cognitive Functions, Cognitive Neuroscience, Neuroscience Revolution, Decision-Making Processes.

1-Introduction

Today, a huge revolution has taken place in the field of cognitive neuroscience, which studies the biological processes and biological aspects that occur in the brain in the cognitive process, and its main focus is on the neuronal connections inside the brain, which play a role in mental processes. Cognitive neuroscience answers the question of how the cognitive activities that take place in the brain are influenced or controlled by neuronal circuits. Cognitive neuroscience is a sub-branch of both neuroscience and psychology, which share different fields such as behavioral neuroscience, cognitive psychology, physiological psychology, and emotional neuroscience. Recently, cognitive neuroscience has experienced unprecedented growth in the availability of large-scale datasets. These developments hold great methodological and theoretical promise: they allow increased statistical power, the use of nonparametric and generative models, the examination of individual differences, and more [1] Cognitive neuroscientists employ clever experimental manipulations in hopes of discovering interpretable relationships between the brain, behavior, and the environment. There is a commitment —often implicit —in both our scientific thinking and writing that the models we derive from tightly-controlled experimental manipulations will provide [2] Cognitive neuroscience has developed rapidly and made significant advances since its emergence in the 1980s. Its application to legal fields in the 1990s led to the intersection of law and cognitive neuroscience. This has been termed 'neurolaw' (Hirsch, 2003). Cognitive solutions are designed to construct legal predictive models that are closely aligned with judicial reasoning, and to provide logical arguments to clarify and justify decision outcomes. The integration of cognitive science with psychology, AI, neuroscience, linguistics, anthropology and even natural philosophy can process large amounts of data and have a good understanding of the processes [3].

According to recent studies and developments, we found that there is no doubt that cognitive neuroscience and educational sciences are two fruitful research fields. In recent years, they have extended existing theories and helped to inform practitioners. Cognitive neuroscience has contributed to increasing our knowledge about human processes and skills [4]. And it is interesting to know that through eye tracking, gaze location can be objectively measured from children as young as a few days old, and up to adulthood. As such, eye tracking has been one of the main research methods in the last decades for gaining insights into early (neuro) cognitive development (see e.g. Aslin and McMurray, 2004; Aslin, 2012; Oakes, 2012). Eye tracking is therefore also one of the main methods used in the YOUth study investigating individual developmental trajectory [5]. It's good to know: a fundamental goal in neuroscience is to discover how the human brain understands and produces language. The methods used to study processes in the human brain have advanced considerably over the past decades. Advancements in neuroimaging and neural recording technologies have made it possible to measure brain responses with higher fidelity and spatio- temporal resolution, and modern analysis techniques have made it possible to analyze larger and more complex datasets. Yet many—if not most—experimental designs in neurolinguistics are still rooted in the techniques of the past: comparing brain responses to isolated words or simplified sentences [6].

Nastase et al, (2020) investigated that, rethinking the primacy of experimental control in cognitive neuroscience and their results revealed that, Naturalistic experimental paradigms in neuroimaging arose from a pressure to test the validity of models we derive from highly-controlled experiments in real-world contexts. In many cases, however, such eff orts led to the realization that models developed under particular experimental manipulations failed to capture much variance outside the context of that manipulation. The critique of non-naturalistic experiments is not a recent development; it echoes a persistent and subversive thread in the history of modern psychology. The brain has evolved to guide behavior in a multidimensional world with many interacting variables. The assumption that artificially decoupling and manipulating these variables will lead to a satisfactory understanding of the brain may be untenable. We develop an argument for the primacy of naturalistic paradigms, and point to recent developments in machine learning as an example of the transformative power of relinquishing control. Naturalistic paradigms should not be deployed as an afterthought if we hope to build models of brain and behavior that extend beyond the laboratory into the real world [2].

Aldous (2007), considered that, Insights from history, cognitive psychology and neuroscience and his results revealed that, examines the intersection between creativity, problem solving, cognitive psychology and neuroscience in a discussion surrounding the genesis of new ideas and innovative science. Three creative activities are considered. These are the interaction between visual-spatial and analytical or verbal reasoning, attending to feeling in listening to the 'self', and the interaction between conscious and non- conscious reasoning. Evidence for the importance of each of these activities to the creative process is drawn from historical and introspective accounts of novel problem solving by noted scientists and mathematicians; cognitive psychology and neuroscience; and a recent empirical study of novel mathematics problem solving. An explanation of these activities is given in terms of cognitive neuroscience. A conceptual framework connecting each of these activities is presented and the implications for learning and teaching considered [7].

Hessels and Hooge (2019), conducted eye tracking in developmental cognitive neuroscience and their results revealed that eye tracking is a popular research tool in developmental cognitive neuroscience for studying the development of perceptual and cognitive processes. However, eye tracking in the context of development is also challenging. In this paper, we ask how knowledge on eye-tracking data quality can be used to improve eye-tracking recordings and analyses in longitudinal research so that valid conclusions about child development may be drawn. We answer this question by adopting the data-quality perspective and surveying the eye-tracking setup, training protocols, and data analysis of the YOUth study (investigating neurocognitive development of 6000 children). We first show how our eye-tracking setup has been optimized for recording high-quality eye-tracking data. Second, we show that eye-tracking data quality can be operator-dependent even after a thorough training protocol. Finally, we report distributions of eye-tracking data quality measures for four age groups (5 months, 10 months, 3 years, and 9 years), based on 1531 recordings. We end with advice for (prospective) developmental eye-tracking researchers and generalizations to other methodologies [5].

Hamilton and Huth (2018), examined natural stimuli in speech neuroscience and their results revealed that humans have a unique ability to produce and consume rich, complex, and varied language in order to communicate ideas to one another. Still, outside of natural reading, the most common methods for studying how our brains process speech or understand language use only isolated words or simple sentences. Recent studies have upset this status quo by employing complex natural stimuli and measuring how the brain responds to language as it is used. In this article we argue that natural stimuli offer many advantages over simplified, controlled stimuli for studying how language is processed by the brain. Furthermore, the downsides of using natural language stimuli can be mitigated using modern statistical and computational techniques [6].

Ni Zhang and Zixuan Zhang (2023), perused the application of cognitive neuroscience to judicial models and their results revealed that, Legal prediction presents one of the most significant challenges when applying artificial intelligence (AI) to the legal field. The legal system is a complex adaptive system characterized by the ambiguity of legal language and the diversity of value functions. The imprecision and procedural knowledge inherent in law makes judicial issues difficult to be expressed in a computer symbol system. Current semantic processing and machine learning technologies cannot fully capture the complex nature of legal relations, thereby raising doubts about the accuracy of legal predictions and reliability of judicial models. Cognitive computing, designed to emulate human brain functions and aid in enhancing decision-making processes, offers a better understanding of legal data and the processes of legal reasoning. This paper discusses the advancements made in cognitive methods applied to legal concept learning, semantic extraction, judicial data processing, legal reasoning, understanding of judicial bias, and the interpretability of judicial models. The integration of cognitive neuroscience with law has facilitated several constructive attempts, indicating that the evolution of cognitive law could be the next frontier in the intersection of AI and legal practice [3].

According to the recent studies in the field of cognitive neuroscience, this review study found that a great revolution has occurred in these sciences, with which we can help people in the society, and by studying developmental cognitive neuroscience, cognitive and perceptual processes, and the emergence of new ideas and innovative science, we hope to have achievements in this article. The purpose of writing this article is that in relation to the achievements in the field of cognitive neuroscience, we obtain information that shows us in what subjects this field can help us to live an easier life or has shown us You will see how it works together with other disciplines and you will understand what extraordinary things can be done with this science.

2-Methodology

In current scholar first of all try to review each the main and foremost method of each papers carefully, for this reason the method that used by each Scholars are as follows:
The first research belongs to the Hessels and Hooge (2019), applied Eye tracking in developmental cognitive neuroscience and they analyzed some variable parameters including the YOUth study (YOUth is a large scale, longitudinal cohort following nearly 4,000 Dutch children in their development from pregnancy until early adulthood). The YOUth study is a large cohort study involving two cohorts (0–6 years and 9–15 years) with a projected 3000 participants in each. At each visit, multiple measurements are conducted, among which eye tracking, EEG, questionnaires, behavioral tasks, observation of parent- child interaction, biological material, and fMRI. The exact measurements conducted at each time point vary with age. Recruitment for the YOUth study commenced in 2015 and is still ongoing. Participants are recruited in Utrecht and its neighboring communities. The YOUth study was approved by the Medical Research Ethics Committee of the University Medical Center Utrecht and all participants’ parents' pro- vided written informed consent. Detailed in- formation on the YOUth study design, in- and exclusion criteria, and the measurements conducted at each timepoint is forthcoming in this special issue.
For the present paper, 500 eye-tracking data sets were requested from the YOUth study for each available age group (5 months, 10 months, 3 years, 9 years). As the 3-year wave has only recently commenced, only 31 sets were available at the time of writing [5].
The second research, Sutil-Martín and Rienda-Gómez (2020), conducted The Influence of Unconscious Perceptual Processing on Decision-Making and they analyzed some variable parameters including the following independent variables were considered: personality (degree of neuroticism, extroversion– introversion), subliminal stimulus type (verbal or pictorial), and gender of individuals. The influence in decision-making was the dependent variable. The population chosen consists of individuals between the ages of 18 and 25, belonging to the demographic cohort “Generation Z” (Zheng, 2018) living in Madrid, and who have a profile on a social network. People within this cohort are generally more active on social networks, tend to follow several “instagrammers” and “influencers,” own smartphones, tend to follow trends in fashion closely, and are more permeable to unconscious perceptual processes (Fromm and Read, 2018). The experiment was conducted between September and October 2018. A non-experimental, exploratory, correlational, and cross-sectional design was carried out by means of a horizontal networking sampling, a social networking that usually starts with a multiple (although relatively small) number of initial contacts and then uses these to establish links with other research participants (Geddes et al., 2018) via social media like Twitter and Instagram. Horizontal networking uses both strong and weak ties to bridge into new social networks, casting the sampling and recruitment net wide rather than deep (Talón-Ballestero et al., 2019). To test the hypotheses, a set of ANOVA univariate general linear model (GLM) models (GLM is a flexible generalization of ordinary linear regression. GLM generalized linear regression by allowing the linear model to be related to the response variable via a link function and by allowing the magnitude of the variance of each measurement to be a function of its predicted value) (Bruno et al., 2020) and logistic regressions were run (table1 and table2). The univariate GLM procedure provides regression analysis and analysis of variance for one dependent variable by one or more factors and/or variables. The factor variables divide the population into groups (table3 and table 4). Using this GLM procedure, we were able to test the null hypotheses about the effects of other variables on the means of various groupings of a single dependent variable. We were also able to investigate interactions between factors as well as the effects of individual factors, some of which may be random [8].

Table 1- ANOVA univariate model: Cow-Brav

Origin	Type III sum of squares	df	Squared mean	F	Sig.
Adjusted model	1.763	3	0.588	2.663	0.050*
Intercept	2.758	1	2.758	12.501	0.001***
PC_N	0.562	1	0.562	2.545	0.113
PC_I	0.121	1	0.121	0.551	0.459
Gender	1.363	1	1.363	6.178	0.014**
Error	32.878	149	0.221		
Total	53.000	153			

*R-squared = 0.051 (R-squared adjusted = 0.032) Dependent Variable: Cow_Brav. Sig. Codes: ***0.001, **0.01, *0.1.*

Table 2- ANOVA univariate model: Male-Female

Origin	Type III sum of squares	df	Squared mean	F	Sig.
Adjusted model	22.551	3	7.517	73.696	0.000***
Intercept	0.232	1	0.232	2.271	0.134
PC_N	1.440	1	1.440	14.122	0.000***
PC_E	0.022	1	0.022	0.215	0.644
Gender	21.003	1	21.003	205.916	0.000***
Error	15.300	150	0.102		
Total	67.000	154			

*R-squared = 0.596 (R-squared adjusted = 0.588) Dependent Variable: Male_Female. Sig. Code: ***0.001.*

Table 3- Binary logit model: Cow-Brav

	Coefficients	Statistic error	Wald	df	Sig.	Exp(B)
Gender	0.935	0.372	6.307	1	0.012*	2.548
PC_N	−0.009	0.007	1.590	1	0.207	0.991
PC_E	0.012	0.009	1.695	1	0.193	1.012
PC_I	0.004	0.007	0.417	1	0.518	1.004
VR_CV	−0.169	0.374	0.204	1	0.652	0.845
Intercept	−1.597	0.994	2.582	1	0.108	0.202

*Sig. Code: *0.1.*

Table 4- Binary logit model: Male-Female

	Coefficients	Statistic error	Wald	df	Sig.	Exp(B)
Gender	−4.927	0.802	37.769	1	0.000***	0.007
PC_N	0.052	0.014	13.801	1	0.000***	1.053
PC_E	0.014	0.015	0.810	1	0.368	1.014
PC_I	−0.013	0.013	1.164	1	0.281	0.987
VR_MF	2.089	0.616	11.498	1	0.001***	8.079
Intercept	−2.455	1.581	2.410	1	0.121	0.086

*Sig. Code: ***0.001.*

The third scholar in this case is Piwowarski et al, (2019) investigated The Cognitive Neuroscience Methods in the Analysis of the Impact of Advertisements in Shaping People's Health Habits and they analyzed some variable parameters including thirty healthy volunteers participated in the study. Before starting the study, the participants were informed about its course and which devices (non-invasive) will be connected. However, they were not informed about the details of the experiment (what it will concern). The procedure was carried out in accordance with guidelines approved by the appropriate Research Ethics Committees. Prior to the start of the study, the participant of the experiment signed a document certifying about conscious participation in the research and agreed to participate. The study was conducted in accordance with the principles published in the Helsinki declaration of 1975 (“World Medical Association Declaration of Helsinki,” 2013). The collected measurement data (EEG, GSR, and HR) were used to individually assess the reception of stimuli emitted during the displayed experimental task. While watching the video and ads, the participants were not aware that a few hours after the end of the measurements the survey will be carried out with them. The questionnaire appeared on what they remembered (advertisements, scenes from commercials), whether advertisements appeared specific brands, products, services, and how they relate to selected issues (the need to carry out vaccinations, the effectiveness of vaccines, etc.). Participants of the study once again looked at the ads and evaluated each of them (whether it is understandable, whether it is convincing, if they like it, etc). The plot of the advertisement includes such scenes as: shows a cozy children's room, carrying out a child's bed from the room and turning off the lamp, a room that looks like a hospital space (hall), information about recommended vaccinations, again a small children's room with parents. The pharmaceutical company responsible for the advertising is assuming that this advertising is campaigned for social awareness (information and education) and encouraging the children vaccination [9].

3-Results and Discussions

Hessels and Hooge (2019), reported Eye tracking in developmental cognitive neuroscience and the results of their research were very useful, so I will discuss them in detail.
1. The eye-tracking setup in the YOUth study
Figure1. Depicts the setup developed for the YOUth study. It is a custom design, built by a professional constructor according to the needs specified by the eye-tracking researchers in the YOUth cohort study. It consists of an eye tracker mounted to a moveable frame and a platform with two different seats mounted on it. The eye tracker they chose to use in the YOUth study is the Tobii TX300. This decision was based on extensive testing of different eye trackers on their robustness to participant movement and non-optimal head orientation relative to the eye tracker (Hessels et al., 2015b; Niehorster et al., 2018). The eye tracker is mounted underneath a computer screen. As such, the optimal position and orientation between participant and eye tracker can be achieved by (1) orienting the computer screen parallel to the participant's head, and (2) positioning the computer screen at the right distance and height relative to the participant's line of sight when looking straight ahead. As denoted by the yellow arrow in Panel A in Fig. 2, the computer screen and eye tracker can be lowered and heightened. As denoted by the blue arrow, it can furthermore be tilted from fully vertical to fully horizontal relative to the floor. It is thus possible to position and orient the eye tracker optimally with respect to the participant with many different types of seating,3 for example with a small infant car seat (Panel C) or a slightly larger car seat (Panel B). It is also possible to position the eye tracker fully upright and use it with older children or adult participants positioned in a chin rest. This setup makes it possible to conduct eye-tracking research with participants from infancy to adulthood. In order to facilitate quick positioning of the children, two car seats are mounted on a wheeled platform: one seat for infants, one for larger infants or toddlers. Both seats afford little participant movement. The wheeled platform makes it easy to fine tune the exact positioning of the child, without having to ask a parent to move, or to move the eye-tracker and its frame. In sum, the presented setup satisfies all criteria we noted in the Methods section.

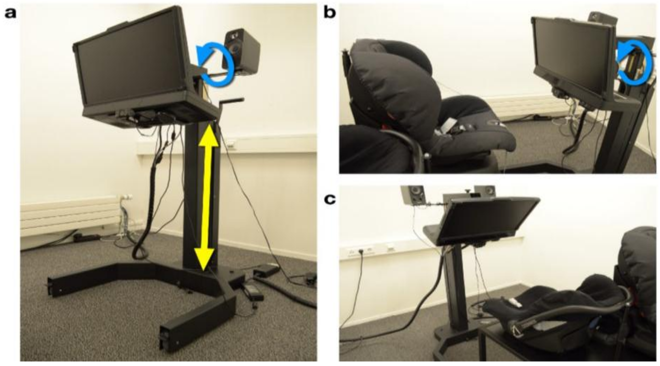

Figure 1- (a) Eye-tracking setup used in the YOUth cohort study for ages 0 and up. The eye tracker (Tobii TX300) is mounted in a frame that can be lowered and heightened (indicated by the yellow arrow). The eye tracker can be tilted from fully vertical to fully horizontal (indicated by the blue arrow), such that the optimal relative position and orientation between eye tracker and participant can be achieved with almost all manners of seating. (b) The setup as it is generally positioned with larger infants and toddlers. (c) The setup as it is generally positioned with young infants. The seats in (b) and (c) are mounted on a platform with wheels. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

2. Eye-tracking data quality for multiple research assistants

Figure2. Depicts distributions of the estimates for precision and data.They are aware of the fact that there are developmental eye-tracking re- searchers who prefer not to use a car seat as infants may cry more in a car seat than e.g. on the parent’s lap. While their first choice is the use of a car seat to minimize infant movement, they opt for either a high chair or placing the infant on the parent's lap when the infant does not tolerate the car seat or when the parent informs the RA that the infant will not tolerate the car seat. Loss for the 5-month-old and 10-month-old infants, as recorded by the 5 RAs that conducted the most recordings per age group. Each participant contributes one value to a distribution. In order to ease visual com- parison of the distributions, they were kernel-smoothed in MATLAB.4 as visible from the top left panel in Fig. 2, the distribution of precision for 5-month-old infants was not identical for every RA. For RAs 3 and 4, for example, the peak of the distribution is close to 1.5° of RMS-s2s deviation, while it peaks around 1° for RAs 1 and 2. This is not the case for 10-month-old infants as seen from the top right panel, at least not to the same extent. Here, the distributions peak roughly at the same value for all RAs. As the distributions overlap for a large part, statistical analysis was conducted to support these findings. A one-way Bayesian ANOVA was conducted in JASP (JASP Team, 2018) for the RMS s2s values with RA as a fixed factor. This was done separately for the 5- month-old and 10-month-old infants. For the 5-month-old infants, the model including the RA factor was best supported by the data, as indicated by a Bayes Factor (BFM, where M denotes the model described) of 6.5 * 104. This indicates that the RA affects the RMS s2s value. For the 10-month-old infants, the null model was supported best by the data, albeit only slightly (BFM = 2.66). For data loss, a similar pattern is observed. As visible from the bottom left panel in Fig. 3, the distributions of data loss for 5-month-old infants have a sharp peak at around 0.15 for RAs 1 and 5, while the distributions are much wider for RAs 2, 3 and 4. For the 10-month-old infants (bottom right panel), the distributions of data loss of the RAs peak closer together. These findings were again supported by statistical analysis. One-way Bayesian ANOVAs were conducted for the proportion of data loss values with RA as a fixed factor, separately for the 5-month- old and 10-month-old infants. For the 5-month-old infants, the model including the RA factor was best supported by the data (BFM = 6.06). For the 10-month-old infants, the null model was supported best by the data (BFM = 75.01). These findings indicate that eye-tracking data quality may be dependent on the RA. Here, eye-tracking data quality was RA-de- pendent for the younger infants (5 months) but not for the older infants (10 months). It should be noted, however, that the RAs were not the same for the 5-month-old and 10-month-old infants. The reason for this is that only two RAs that conducted more than 30 measurements for the 5-month-old infants also conducted more than 30 measurements for the 10-month-old infants. When fewer than 30 measurements are available, estimates of precision and data loss for an RA are unreliable, as they can be too dependent on a few ‘easy-’ or ‘difficult-to-record’ infants. However, in order to check that both age and RA experience contribute to eye-tracking data quality, and differences between age groups are not due to different RAs, a Bayesian ANOVA was conducted for the two RAs that contributed measurements to both age groups. For the estimates of precision, this revealed that the model including both the participant age group and the RA as a factor was best supported by the data (BFM = 22.26). For the estimates of data loss, the model including only the participant age group was best supported by the data (BFM = 3.37), followed closely by the model including both participant age group and RA (BFM = 2.48). Eye-tracking data quality is thus dependent on both participant age and which RA conducts the measurement. Another interesting finding is that it is not necessarily the case that more experienced RAs, i.e. those with more recordings to their name, are the ones with the best eye-tracking data quality for their recordings. The ‘best’ distribution for both measures of eye-tracking data quality is one that peaks early and does not have a long tail to the right. For the precision observed with 5-month-old infants, RA 2 fits this description best, followed by RA 1 and RA 5, showing that more experienced operators produced better eye-tracking data quality. However, for the data loss observed with

5-month-old infants, RA1 and RA 5, not RA 2, fit this description best. For the 10-month-old infants, this comparison is more difficult to make, as the distributions are more alike.

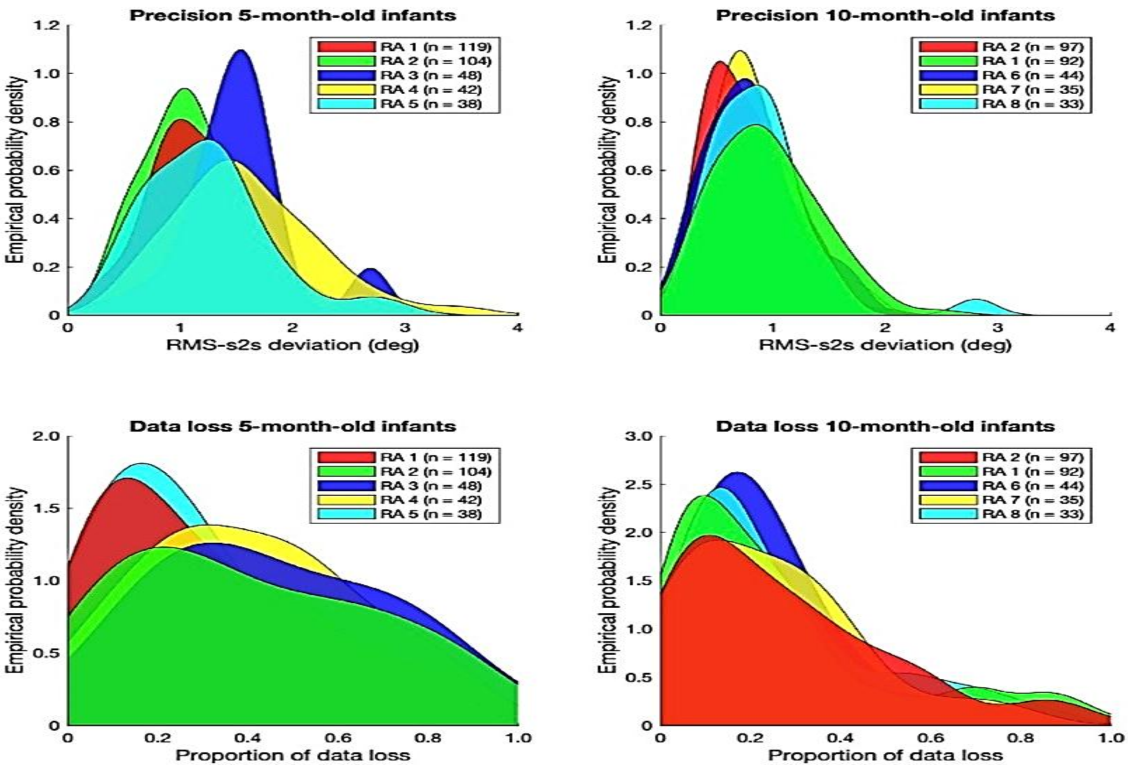

Figure 2- Distributions of the estimates for precision for 5-month-old infants (top left) and 10-month-old infants (top right) and data loss for 5-month-old infants (bottom left) and 10-month-old infants (bottom right).

3. Eye-tracking data quality ranges in developmental eye-tracking research

Figure3. Depicts distributions of the RMS-s2s deviation (estimate for precision) and proportion of data loss for the four age groups. Each participant contributes one value to a distribution. As is visible from the left panel, the distribution of RMS-s2s deviation peaks around 1 to 1.5° for the 5-month-old infants, while it peaks increasingly earlier for the 10-month-old infants, the 3-year-old children and the 9-year-old children. A similar pattern is observed for the proportion of data loss (right panel in Fig. 3). Here, the distribution for the 5-month-old infants is very wide, with no clear peak. For the older ages (10 months, 3 years and 9 years), the distribution is increasingly more peaked towards the lower values, indicating better eye-tracking data quality. Note that for both RMS-s2s deviation and the proportion of data loss, the distributions are wider for younger children than for older children. This means that the differences in data quality are larger between the eye-tracking data of the younger participants, than the eye-tracking data of the older participants. They further investigated differences in data loss across ages, by looking at data loss for the individual eyes. Ideally, data loss is 0 for both eyes, indicating that a gaze position could always be reported for each eye. However, data loss is inevitable and particularly so in developmental eye-tracking research. If a participant blinks, for example, a gaze coordinate cannot be reported for a short period (generally a few hundred milliseconds at maximum). If a participant looks away from the eye tracker completely, a gaze coordinate can also not be reported. Such episodes are likely to occur with infants or toddlers. However, data loss can also occur when a participant is not blinking or looking away. As stated, such data loss may occur due to technical difficulties in tracking the eyes (Wass et al., 2014; Hessels et al., 2015a), for example, when a pupil cannot be found in the camera image of the eye tracker. When a participant blinks or looks away, data loss occurs for both eyes at the same time. If all data loss in a given experiment is due to blinks or looking away, one would thus expect the proportion of data loss to be nearly identical for the two eyes. This does not need to be the case when data loss occurs for different reasons. As visible from the top right panel, the

proportion of data loss for 10-month-old infants also ranges from 0 to 1, but the spread around the unity line is substantially smaller. For the 3-year-old and 9-year-old children (bottom two panels), the spread around the unity line further decreases, and the proportion of data loss clusters more in the bottom left corner of the plot. These findings can be de- scribed by two metaphorical forces. As children age, the proportion of data loss is forced towards the unity line, and towards 0 (the bottom left corner of the plot). In other words, as children age the proportion of time that only one eye can be tracked is reduced and the amount of data loss that occurs at all. This furthermore indicates that the higher levels of data loss for the 5-month-old infants compared with the 10-month- old infants are not likely due to more looking away from the screen, which would lead to both eyes not being tracked instead of only one [5].

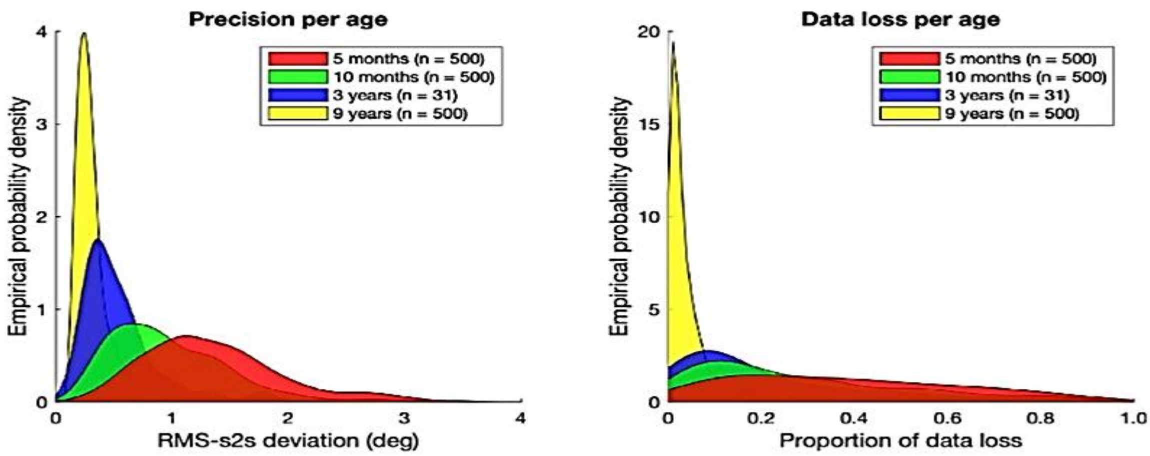

Figure 3- Distributions of the estimates for precision (left) and data loss (right) for the four different age groups: 5 months, 10 months, 3 years, and 9 years. Precision was estimated by the Root Mean Squared sample-to-sample deviation (RMS s2s) of the gaze-position signals

Sutil-Martín and Rienda-Gómez (2020), investigated The Influence of Unconscious Perceptual Processing on Decision-Making and their article’s results included: motivated by the gap detected in the literature regarding the role of gender and personality traits in response to subliminal messages and in unconscious processes. Previous studies have followed two broad approaches: the first with personality variables and unconscious decision-making processes, subliminal messages, and visual masking or semantic priming techniques and the second with verbal and pictorial messages, using the same techniques, but without considering the personality characteristics or the gender of individuals. By contrast, this study has dealt simultaneously with different subliminal messages, both verbal and pictorial, personality traits, and gender. For decision-making purposes, it is important to know if males or females are more likely to be influenced by subliminal messages and whether these have measurable effects on their behavior. Furthermore, different personality traits can affect this influence. Therefore, it would be advisable for digital marketers like “influencers” and “instagrammers” to become aware of these direct specific actions aimed at certain objectives to strengthen loyalty in their brands and make marketing campaigns more effective.

In view of the results obtained, it can be confirmed, unlike in previous studies where techniques such as the use of fMRI were not applied, that unconsciously processed information can influence decision-making. The verbal stimulus and levels of neuroticism show statistically significant impacts in measuring the effect of behavior on the unconscious decision-making process. Neither extroversion nor introversion was shown to be relevant for this unconscious decision- making processes, under either of the two stimuli. Under the experimental conditions, the subliminal verbal stimulus was more effective than the pictorial stimulus, as recent research has shown. In an attempt to investigate this result and, in particular, the bias toward associating the human figure (pictorial stimulus) as a coward in the responses of the experimental groups, we asked if there was a feature of the figure that made them think it was cowardly. The participants answered that the human figure had a hand in his pocket, which signified that he was hiding something and therefore was a coward. This response must be considered in a subsequent investigation.

Gender has a measurable effect for both verbal and pictorial stimuli. However, for the pictorial stimulus, we can only conclude that the behavior is different for males and females, observing that being male increases the probability of stating that the individual in the human figure is brave but without reflecting statistical significance. For the verbal stimulus, the gender variable is highly significant, in addition to representing a measurable effect together with the actual stimulus. This paper presents several limitations that will guide the development of future research. The results are limited to Spanish Twitter users and the way they follow “influencers,” “youtubers,” and “instagrammers.” Therefore, the evidence shown in this paper cannot be generalized to different social media or geographical contexts. Moreover, it is necessary to develop a broader study considering other personality traits, following a model different from Eysenck’s theory, and adding other variables like extended age range, social status, and economic resources. Another limitation is the way the videos were presented and the time between subliminal messages. Due to the technical characteristics of the devices used, the presentation time did not allow us to decrease the presentation time of the subliminal stimuli, which might have influenced the direction of the response [8].

Piwowarski et al, (2019) conducted The Cognitive Neuroscience Methods in the Analysis of the Impact of Advertisements in Shaping People's Health Habits and The results obtained from their research are as follows:

Cognitive neuroscience methods have a huge research potential not only in the field of neuromarketing, but also in other areas of economics (decision making, risk aversion, etc.). The popularity of these methods come from the possibility of observing psychophysiological functions of the human being and accurate objective measurement of the body's response to specific external stimuli. Such methods allow to build knowledge about a human behavior already at the level of internal psychophysiological and cognitive processes before they are integrated and verbalized in the form of an opinion expressed on a given topic. In the context of study, the advertising message can bring specific benefits related to the evaluation of a given spot including the assessment of the effectiveness of the message's specific content, e.g. pro-health. With their help, we can analyze individual parts of advertising spots, explore how they affect people. One can study emotional reactions, levels of remembering or interest. One can also set other metrics, for example involvement or fatigue. Having such detailed knowledge about the human response to a given advertising message can effectively increase the quality of this message. Inefficient scenes with low impact on the recipient can be redesigned. Longer advertising spots can be shortened by removing relevant parts of it. This can have a direct impact on the reduction of advertising costs (shorter advertising - lower emission costs). The specificity of social advertising, especially aimed at promoting health habits often means that it contains scenes with a high emotional basis. In this context, selected methods of cognitive neuroscience (such as EEG, GSR, HR) work well. The advertisement analyzed in this article encouraging to carry out preventive vaccination did not reach a sufficiently high threshold of expression agents [9].

4-Conclusion

By examining the great revolution of neuroscience, eye tracking was done in the age range of 5 to 10 months old babies and teenagers in standard conditions, and we found that errors and loss of information decrease as children age. The proportion of data loss for 10-month-old infants also ranges from 0 to 1, for the 3-year-old and 9-year-old children, the spread around the unity line further decreases, and the proportion of data loss clusters more in the bottom left corner of the plot. These findings can be de- scribed by two metaphorical forces. As children age, the proportion of data loss is forced towards the unity line, and towards 0 (the bottom left corner of the plot). The effect of unconscious perception on decision-making is great, and as much as perception can affect our lives, our introversion and extroversion cannot. we can only conclude that the behavior is different for males and females, observing that being male increases the probability of stating that the individual in the human figure is brave but without reflecting statistical significance. Neuromarketing technique, we can be effective in terms of their health habits by considering the level of people's emotions. The specificity of social advertising, especially aimed at promoting health habits often means that it contains scenes with a high emotional basis.

5-References

1. Tibon, R., Geerligs, L., & Campbell, K. (2022). Bridging the big (data) gap: levels of control in small-and large-scale cognitive neuroscience research. Trends in Neurosciences.

2. Nastase, S. A., Goldstein, A., & Hasson, U. (2020). Keep it real: rethinking the primacy of experimental control in cognitive neuroscience. NeuroImage, 222, 117254.

3. Zhang, N., & Zhang, Z. (2023). The application of cognitive neuroscience to judicial models: recent progress and trends. Frontiers in Neuroscience, 17, 1257004.

4. Basso, D., & Cottini, M. (2023). Cognitive Neuroscience and Education: Not a Gap to Be Bridged but a Common Field to Be Cultivated. Sustainability, 15(2), 1628.

5. Hessels, R. S., & Hooge, I. T. (2019). Eye tracking in developmental cognitive neuroscience–The good, the bad and the ugly. Developmental cognitive neuroscience, 40, 100710.

6. Hamilton, L. S., & Huth, A. G. (2020). The revolution will not be controlled: natural stimuli in speech neuroscience. Language, cognition and neuroscience, 35(5), 573-582.

7. Aldous, C. R. (2007). Creativity, problem solving and innovative science: Insights from history, cognitive psychology and neuroscience.

8. Sutil-Martín, D. L., & Rienda-Gómez, J. J. (2020). The influence of unconscious perceptual processing on decision-making: A new perspective from cognitive neuroscience applied to generation z. Frontiers in Psychology, 11, 1728.

9. Piwowarski, M., Shankar Singh, U., & Nermend, K. (2019). The cognitive neuroscience methods in the analysis of the impact of advertisements in shaping people's health habits.