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LOW-COST PORTABLE WIRELESS ELECTROENCEPHALOGRAPHY TO DETECT EMOTIONAL RESPONSES TO VISUAL CUES - VALIDATION AND POTENTIAL APPLICATIONS

AHMED MAREY

The American University in Cairo (AUC), Egypt, ahmedmarey@aucegypt.edu

SHERIF GOUBRAN

The American University in Cairo (AUC), Egypt, sherifg@aucegypt.edu

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Abstract

This paper validates the using a low-cost EEG headset – Emotiv Insight 2.0 – for detecting emotional responses to visual stimuli. The researchers detected, based on brainwave activity, the viewer’s emotional states in reference to a series of visuals and mapped them on valence and arousal axes. Valence in this research is defined as the viewer’s positive or negative state, and arousal is defined as the intensity of the emotion or how calm or excited the viewer is. A set of thirty images – divided into two categories: Objects and Scenes – was collected from the Open Affective Standard Image Set (OASIS) and used as a reference for validation. We collected a total of 720 data points for six different emotional states: Engagement, Excitement, Focus, Interest, Relaxation, and Stress. To validate the emotional state score generated by the EEG headset, we created a regression model using those six parameters to estimate the valence and arousal level, and compare them to values reported by OASIS. The results show the significance of the Engagement parameter in predicting the valence level in the Objects category and the significance of the Excitement parameter in the Scenes category. With the emergence of personal EEG headsets, understanding the emotional reaction in different contexts will help in various fields such as urban design, digital art, and neuromarketing. In architecture, the findings can enable designers to generate more dynamic and responsive design solutions informed by users’ emotions.

Keywords

Electroencephalography; Emotion Detection; Open Affective Standard Image Set; Emotive Insight

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AHMED MAREY AND SHERIF GOUBRAN

The American University in Cairo (AUC), Egypt
ahmedmarey@aucegypt.edu
sherifg@aucegypt.edu

ABSTRACT

This paper validates the using a low-cost EEG headset – Emotiv Insight 2.0 – for detecting emotional responses to visual stimuli. The researchers detected, based on brainwave activity, the viewer’s emotional states in reference to a series of visuals and mapped them on valance and arousal axes. Valence in this research is defined as the viewer’s positive or negative state, and arousal is defined as the intensity of the emotion or how calm or excited the viewer is. A set of thirty images – divided into two categories: Objects and Scenes – was collected from the Open Affective Standard Image Set (OASIS) and used as a reference for validation. We collected a total of 720 data points for six different emotional states: Engagement, Excitement, Focus, Interest, Relaxation, and Stress. To validate the emotional state score generated by the EEG headset, we created a regression model using those six parameters to estimate the valence and arousal level, and compare them to values reported by OASIS. The results show the significance of the Engagement parameter in predicting the valence level in the Objects category and the significance of the Excitement parameter in the Scenes category. With the emergence of personal EEG headsets, understanding the emotional reaction in different contexts will help in various fields such as urban design, digital art, and neuromarketing. In architecture, the findings can enable designers to generate more dynamic and responsive design solutions informed by users’ emotions.

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ملخص

تتحقق هذه الورقة من استخدام سماعة رأس EEG منخفضة التكلفة - Emotiv Insight 2.0 - لاكتشاف الاستجابات العاطفية للمنبهات البصرية. اكتشف الباحثون ، بناءً على نشاط الموجات الدماغية ، الحالات العاطفية للمشاهد بالإشارة إلى سلسلة من الصور المرئية ورسموها على محاور التكافؤ والإثارة. يتم تعريف التكافؤ في هذا البحث على أنه حالة المشاهد الإيجابية أو السلبية، ويتم تعريف الإثارة على أنها شدة العاطفة أو مدى هدوء المشاهد أو حماسه. تم جمع مجموعة من ثلاثين صورة - مقسمة إلى فئتين: الأشياء والمشاهد - من مجموعة الصور القياسية العاطفية (OASIS) واستخدامها كمرجع للتحقق من صحة النتائج. قُمتنا بجمع ٧٢٠ نقطة بيانات لست حالات عاطفية مختلفة: الانخراط والإثارة والتركيز والاهتمام والاسترخاء والتوتر. للتحقق من درجة الحالة العاطفية الناتجة عن سماعة EEG، أنشأنا نموذجًا للانحدار باستخدام تلك المعلمات الستة لتقدير مستوى التكافؤ والإثارة ، ومقارنتها بالقيم التي أبلغت عنها OASIS. تُظهر النتائج أهمية معلمة المشاركة في التنبؤ بمستوى التكافؤ في فئة الأشياء وأهمية معلمة الإثارة في فئة المشاهد. مع ظهور سماعات رأس EEG الشخصية، فإن فهم رد الفعل العاطفي في سياقات مختلفة سيساعد في مختلف المجالات مثل التصميم الحضري والفن الرقمي والتسويق العصبي. في مجال الهندسة المعمارية، يمكن للنتائج أن تمكن المصممين من إنشاء حلول تصميم أكثر ديناميكية واستجابة تسترشد بمشاعر المستخدمين.

الكلمات المفتاحية: تخطيط كهربية الدماغ، تحديد العاطفة، مجموعة صور القياسية العاطفية، إيموتيف انساي

1. INTRODUCTION

Spaces play a considerable role in affecting human psychological mood, whether positively or negatively (Elsamahy, 2018). The study of the effect of the built environment on the quality of life has been given a continually increasing interest over the past few years due to its importance in regulating psychological mood – especially stress, which is defined as “The non-specific response of the body to any demand made” (Ellison & Maynard, 1992; Selye, 1974, 1977). According to Tugade and Fredrickson (2006), regulating positive emotional experiences promotes resilience to stressful events. On the other hand, Kopp (1989) discusses the importance of controlling negative emotions and distress from a developmental perspective.

The topic of emotional responses has paved its way in the field of neuroscience research. The hypothesis that hedonic items elicit from consumers more intense emotional responses and sensations than utilitarian products has been developed by researchers over the year (Bagozzi et al., 1999; Kempf, 1999; Allen et al., 2005; Hassenzahl, 2018). However, a recent study casts doubt on the fundamental difference between the emotions evoked by hedonistic and utilitarian items, demonstrating that hedonistic offers only elicit stronger feelings in a segment of customers (Drolet et al., 2007). Bettiga et al. (2020) contend that the contradiction is not caused by the absence of emotions in and of themselves but rather by the character of the emotions appraised, which is solely dependent on their empirical assessment.

The sensory information we receive from our environment significantly impacts how we feel and act (Turley & Milliman, 2000). Most studies on human emotional reactions to environmental characteristics still concentrate on several well-defined and restricted sensory aspects of the environment, although we live in highly diffuse multisensory environments and despite growing interest from various application domains (Schreuder et al., 2016). As a result, systematic knowledge concerning effective multimodal interventions that produce desired results is still lacking (Jain & Bagdare, 2011; Oakes & North, 2008; Turley & Milliman, 2000). As we live in a dynamic environment where factors cannot be considered independently, we hypothesize that understanding brainwave activity should overcome the limitations of traditional tools.

In the context of the built environment, emotional regulation through design, despite its significant potential for creating personalized design solutions, remains largely an undeveloped research area. Until now, the study of human emotional responses to visual cues depends heavily on pooled responses to surveys, which require large samples for validation and consequently eliminate individual differences in emotional responses. As such, this study focused on validating an objective low-cost tool, namely portable wireless electroencephalography, in studying human emotional responses to visual cues. While this study focuses on validating the tool, it will pave the road for more personalized design solutions in built spaces.

The paper first presents some background for the topic, highlighting the different models and tools previously employed in such investigations. The methodology of the article is then presented, and the methods utilized in the validation and analysis are justified using recent similar work. Then, the results of the study are presented and discussed. Finally, the conclusion underscores the key findings, discusses their potential applications in the computational design field, and offers recommendations for future studies.

2. BACKGROUND

The circumplex model of affect (Russell, 1980) and its variant (Larsen, 1992) have been readily studied in the literature and were proven reliable in mapping and detecting human emotions. The model explains that emotions are disseminated in “a two-dimensional circular space.” Those two dimensions are defined as arousal (excitement or activation) and valence (positivity or pleasantness). The valence level is represented on the horizontal axis, and the arousal, on the other hand, is expressed on the vertical axis, in which the circle’s center point represents medium valence and arousal levels (Figure 1). The choice of identifying the valence and arousal levels was based on the fact that almost all other emotions can be classified into the

orthogonal dimensions, including the six basic emotions, which are based on the work of Ekman and Friesen (1976). The model is still widely used in emotional studies (Han et al., 2022; Lipovac et al., 2022; Conrad, 2022)

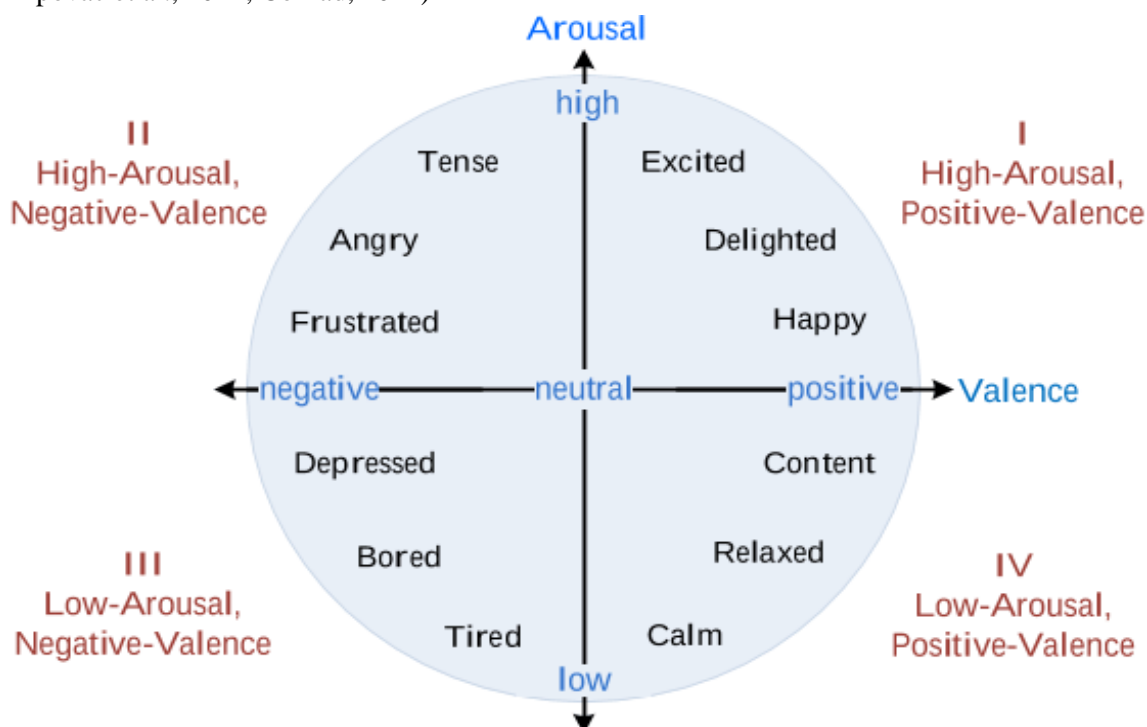


Fig.1: The circumplex model of affect (Russell, 1980)

For psychologists, the concepts of emotion and mood pose a challenge. Although the terms are commonly used interchangeably, most academics concur that the structures they stand for are separate yet closely connected phenomena. In addition, language does not necessarily reflect psychological reality, as Ekman (1994) noted. The fact that we may distinguish between emotion and mood does not necessarily imply that they are different; any distinction may be entirely semantic. The foundation of science is conceptual clarity, and various thinkers have recognized the current jargon confusion (Alpert & Rosen, 1990; Batson, Shaw, & Oleson, 1992; Bless & Schwarz, 1999).

The proposed distinctions cover a wide range of differences, from behavioral and social factors to neurological and physiologic ones. A psychophysicist, like Panksepp (1994), might choose to distinguish the two by contrasting their respective neural or somatic correlates, whereas a psycholinguist, like Wierzbicka (1992), might choose to emphasize semantic distinctions in everyday language. Distinctions are frequently based on the researcher's particular area of interest. Of course, it seems likely that emotion and mood differ along more than one criterion, and it is simple to understand how variations in their underlying physiological processes would result in variations in phenomenal experience, which would then result in variations in expression, behavior, and linguistic descriptions of the two states.

The study of emotional responses to art had its leading tradition, including Daniel Berlyne's psychobiological model, embodied by the "new experimental aesthetics" movement of the 1970s, followed by many pieces of research such as the International Affective Picture System (IAPS) and the Open Affective Standard Image Set (OASIS). All the mentioned pieces of research did not test the viewer's emotional response but instead focused on the emotions embodied in the pictures (i.e., the tests were image-focused, not internal state-focused). In addition, the results were collected from participants using traditional surveys, which are open to subjectivity from participants. Additionally, pooled responses and mean values recorded through surveys tend to eliminate outliers, which could be important to study to understand the variety of emotions different people experience in response to visual cues.

Many published papers focus on emotion detection from facial recognition using artificial intelligence, such as the one presented by Jain et al. (2018). However, Rhue (2018) gives proof that a person's race affects how facial recognition software reads their emotions. The study contrast the emotional analysis provided by two different facial recognition services, Face++ and Microsoft AI, using a publicly accessible data set of images of professional basketball players. Both services perceive black players as more likely to experience negative emotions than white players. Even after accounting for smile intensity, Face++ continually perceives black players as more irate than white players. Microsoft views black players' equivocal facial expressions as more scornful than anger, and it registers contempt as opposed to anger. Garcia and Penichet (2017), there are five main ways for emotion detection – facial expressions, body gestures and movements, psychological state, speech, and text – using technology. For this research and to avoid bias created using AI, we opted for EEG and brainwaves as they would lead to the most accurate results and avoid any racial biases.

Blanco et al. (2019) used low-cost wireless electroencephalography (EEG) headset to quantify the human response on a single-trial basis in relation to various cognitive states. Ramirez et al. (2015) also introduced a neurofeedback approach to treat elderly people diagnosed with depression using music. The users were allowed to manipulate expressive parameters in music performances using their emotional state. The results showed a significant decrease in alpha activity, which can be interpreted as an improvement in the depression state. Li (2020) has stated that emotions are not always detectable using traditional models, and it would be useful if a computer could understand or detect the user's emotions. Emotiv's SDK was utilized, which gave him access to four measurements: Engagement, Excitement, Meditation, and Frustration. Although those measurements were useful for the pilot study, he was concerned by the validity and reliability of those indicators.

Age-related changes in the relationships between the brain and behavior can be studied using a variety of research approaches, according to developmental experts. Many people believe that one of the most effective and reasonably priced techniques for examining these developmental changes is the electroencephalogram (EEG) (Bell & Cuevas, 2012), which is defined as a technique for capturing an electrogram of the scalp's electrical activity, which has been demonstrated to represent the macroscopic activity of the brain's surface layer beneath. According to Bell and Cuevas (2012), scientists like the EEG because it makes it possible to examine developmental changes without significantly affecting continuing normal behaviors. They have employed EEG methods to investigate relationships between brain electrical activity and working memory performance during early childhood (Wolfe & Bell, 2004) and toddlerhood (Bell, 2012, 2001), as well as recall memory performance (Cuevas, Raj, & Bell, 2012). Additionally, we have described the month-to-month variations in infant brain development using EEG (Bell & Fox, 1992, 1994; Cuevas & Bell, 2011).

To conclude the background of this study, we validate utilizing low-cost, portable EEG headsets for the emotional detection of the six measurements indicated before in relation to the valence and arousal reported in the OASIS. Said otherwise, we transform the emotional data received from the EEG headset onto The circumplex model of affect (Russel, 1980). We use a validated set of visual cues, namely the OASIS dataset, to carry out this transformation.

3. METHODOLOGY

3.1. Materials

The images displayed in this study are from OASIS (Kurdi, 2017), which is obtained initially from online sources such as Pixabay, Google Images, and Wikipedia (Kurdi & Banaji, 2016). This set of images was chosen because of their availability and relation to the type of emotions being tested. The standard size of the images is 500 x 400 pixels. 30 images were chosen from the dataset based on three primary criteria. 1) Their valence and arousal levels in order to present the whole spectrum of results (Figure 2). 2) Their standard deviation results from the OASIS dataset to have the minimum variation between

different individuals. 3) Their level of appropriateness to be presented in the culture of the experiment. So, for instance, we opted not to choose images with explicit sexual activity. Also, to ensure that the responses are a mere indication of an instant emotional state, each image was displayed for a maximum of 10 seconds. The images are categorized by 'OASIS's first and second authors "merely to facilitate the use of the stimulus set." The categories used in this study are scenes and objects.

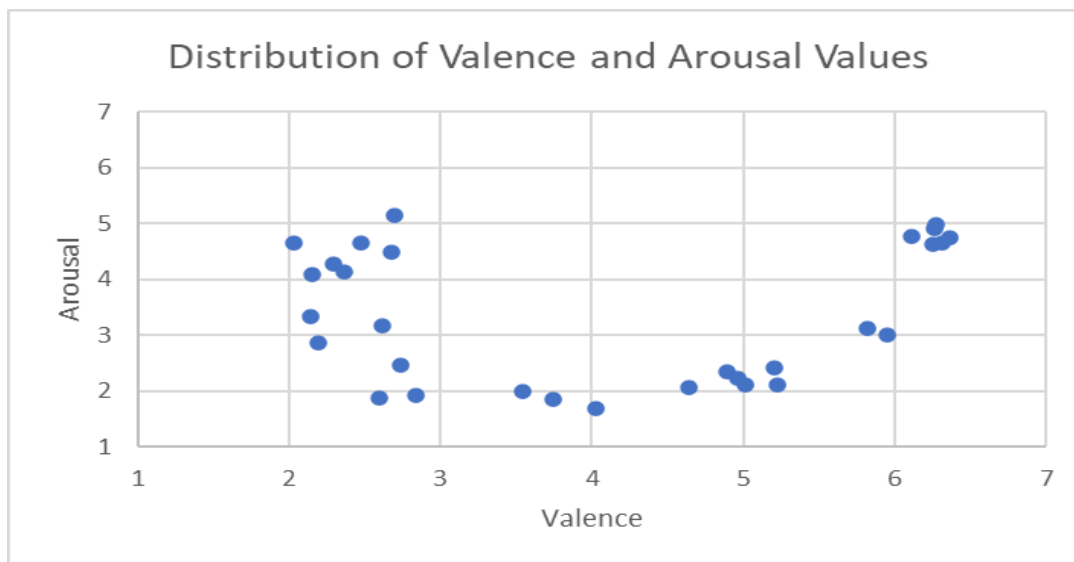


Fig.2: Distribution of Valence and Arousal Values

An Electroencephalography (EGG) headset – Emotiv Insight 2.0 (EMOTIV Insight 2.0 - 5 Channel Mobile Brainwear® - EMOTIV) – was used to translate the participants' psychological signals into six measurements in a 100-grade point system. Those measurements are Engagement, Excitement, Focus, Interest, Relax and Stress. The headset manufacturer provides computer software (EmotivBCI) which – as described by the manufacturer – is a technology that enables you to operate devices directly using your brain activity, as opposed to using a mouse, keyboard, touchscreen, or voice as an intermediary interface. Brain waves are transformed into digital signals via EMOTIV technology, which may then be used to operate an infinite variety of digital outputs, including games, Internet of Things (IoT) devices, communication tools, and audio/visual material. We used the Performance Matrix, which allows passive, ongoing control depending on the current cognitive state, including focus, excitement, interest, engagement, stress, and relaxation indicators.

3.2 Sampling

The first step entailed attaining the approval of the Institutional Review Board at the American University in Cairo. To follow the IRB recommendations, participants were allowed to leave the experiment at any time they felt uncomfortable without giving an explanation.

Two sampling strategies were used for recruiting participants: 1) Quota Sampling, in which random participants are selected, ensuring that specific characteristics – such as gender – are equally represented to reach a more universal result. 2) Referral/Snowball sampling in which participants refer us to others interested in the study as they might be challenging to locate given the current circumstances. Since we do not have the participants contact info, a recruitment survey was open to the public on different platforms in which they provided their contact and demographic information to ensure their eligibility for participating in this research following the quota sampling strategy and the minimum age required – 18. The selected participants were contacted by phone or email, depending on their preference indicated in the recruitment survey, to specify a timing to experiment. The

experiment was conducted in a controlled environment to measure the specified variables without external influences.

3.3 Procedure

Each participant was assigned the 30 chosen images – samples are shown in Figure 3 – from the 900 images dataset. This technique is mainly used to avoid participant fatigue (Fernández-Caballero, 2016). The experiments took place in a closed office environment, and each participant was examined individually to prevent any unexpected data contamination. The participants would be seated comfortably in a chair facing a large screen and were asked to relax and breathe. The research team greeted the participants pleasantly to reduce their stress. Before wearing the headset, the participants are given a general description of the study and the definition of the different aspects being measured. The headset was then placed, and the contact of the sensors on the participant's head using the provided software.



Fig.3: Sample Images

Each image was shown to four participants, and their brainwave activities were recorded along with the images being displayed. Additionally, the research team took notes of any abnormal activity conducted on the software as it might result from an external factor, which further helped the data modeling process. After the completion of the experiment, participants were asked to fill out a standard questionnaire, including gender, age, etc. They also had an exit interview in which they were asked about their overall feedback on the experiment and how to improve the surrounding conditions if possible. Due to the time constraints, we could present the result of four participants: 3 females and 1 male. We also cross-referenced the result and found no significant variation between the two genders in the six aspects tested.

3.4 Data Analysis

The images used in this study can be divided into two categories according to Kurdi (2017): Objects and Scenes. Each of these categories was studied independently to have more accurate results and insights into the triggers of emotional responses. The six emotional states were tested to see if there is any direct correlation between them and the valence and arousal values indicated by OASIS, and a linear regression model using the six emotional responses was created to identify the prediction accuracy of those responses in relation to valence and arousal levels in the two indicated categories.

4. RESULTS

First, we tested the results' normality for the six emotional states – Engagement (En), Excitement (Ex), Focus (Fo), Interest (In), Relax (Re), and Stress (St) – using Shapiro–Wilk test. The results showed that distributions for En, Ex, Re, and St indicate a significant departure from normality, so we concluded that the distributions are not normal. Second, we analyzed the correlations between those parameters and the score values reported by OASIS dataset for valence and arousal using Spearman's rho for nonparametric data and Pearson for parametric data. The results also showed no direct correlation between any of the six emotional states tested and valence or arousal values extracted from OASIS. We opted to create multiple linear regression models for estimating valence and arousal values using the six parameters. Two

models were created for the valence estimation: each for a category of images and the same for arousal estimation. Results of valence prediction are shown in Tables 1 and 2.

Table 1: Significance of Coefficients to estimate valence in the scenes category

Coefficients ^{a,b}

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-20.095	14.996		-1.340	.205
	En-mean	.204	.158	.527	1.290	.222
	Ex-mean	-.203	.098	-.924	-2.072	.060
	Fo-mean	-.289	.184	-.367	-1.572	.142
	In-mean	.547	.290	.458	1.887	.084
	Re-mean	.091	.263	.281	.347	.735
	St-mean	.073	.421	.137	.173	.866

a. Dependent Variable: Valence

b. Selecting only cases for which Category = Scenes

The model for the valence estimation in the scenes category yielded an R^2 value of 0.527, which is better than all the correlation values indicated above. On the other hand, the estimation of valence in the objects category yielded an R^2 result of 0.929.

Table 2: Significance of Coefficients to estimate valence in the objects category

Coefficients ^{a,b}

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-46.386	26.006		-1.784	.149
	En-mean	.370	.057	1.184	6.474	.003
	Ex-mean	-.035	.043	-.159	-.812	.462
	Fo-mean	.018	.084	.046	.216	.839
	In-mean	.901	.616	.421	1.464	.217
	Re-mean	.323	.207	.669	1.559	.194
	St-mean	-.559	.379	-.911	-1.475	.214

a. Dependent Variable: Valence

b. Selecting only cases for which Category = Objects

The R^2 values for the arousal regression model for the scenes category and objects category are 0.210 and 0.539, respectively. The coefficients significance results are shown in Table 3 and 4.

Table 3: Significance of Coefficients to estimate arousal in the scenes category

Coefficients ^{a,b}

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4.258	13.172		.323	.752
	En-mean	-.132	.139	-.503	-.952	.360
	Ex-mean	-.029	.086	-.193	-.334	.744
	Fo-mean	.199	.161	.373	1.233	.241
	In-mean	.043	.255	.054	.171	.867
	Re-mean	.260	.231	1.175	1.122	.284
	St-mean	-.307	.370	-.852	-.830	.423

a. Dependent Variable: Arousal

b. Selecting only cases for which Category = Scene

Table 4: Significance of Coefficients to estimate arousal in the objects categoryCoefficients ^{a,b}

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	-53.965	45.885		-1.176	.305
	En-mean	-.008	.101	-.037	-.078	.941
	Ex-mean	.122	.076	.807	1.616	.181
	Fo-mean	.081	.149	.297	.546	.614
	In-mean	1.510	1.086	1.020	1.390	.237
	Re-mean	.564	.366	1.687	1.542	.198
	St-mean	-1.194	.668	-2.813	-1.786	.149

a. Dependent Variable: Arousal

b. Selecting only cases for which Category = Object

The results prove our initial hypothesis that a low-cost, portable EEG headset can be used for emotional detection, especially when the visual cues fall under the category of objects. Also, it is easier to accurately predict valence than to predict arousal using the six emotional states mentioned before. It is also worth noting that there are discrepancies between the significance of different emotions to predict valence or arousal when the category changes. For example, engagement showed the highest significance in predicting valence in the objects category. On the other hand, excitement was the most significant predictor of valence in the scenes category. Similarly, stress showed the highest significance in predicting arousal in the objects category and focus, on the other hand, focus showed the highest significance in the scenes category.

5. DISCUSSION & CONCLUSION

This paper validates the usage of low-cost, portable EEG headsets for emotion detection. The findings support the initial hypothesis and prove that valence and arousal levels can be accurately predicted using six emotional states: Engagement, Excitement, Focus, Interest, Relax, and Stress. The study sets a cornerstone for further research in different fields as the EEG headsets are widely available and expanding as the new “Fitbit for the brain.” Using EEG signals yields unbiased, accurate results, which can be used to inform decisions in a variety of contexts. Also, it opens up the door for emotional regulation. The idea of emotion regulation in multiple contexts has been proposed in previous studies.

David and Oltean (2015) work titled: “Technology use in promoting effective emotion-regulation: Applications in the workplace, parenting and for children” investigated different emotion regulation strategies using virtual reality, robotics ... etc. However, technology was only used to create different contexts and understand the skills required for the regulation. On the other hand, the smart architecture by Fernández-Caballero et al. (2016) showed direct real-time implementation of technologies and frameworks in emotion detection and regulation. However, due to the complexity of their proposal, the multiple monitoring systems they are using, and the sensitivity of the environment they are operating in, it is concluded that the success of such a project is highly dependent on the acceptance of experts and patients.

Using portable, wireless EEG headsets can overcome such a problem. With the emergence of virtual realities and metaverse, understanding the emotional reaction to different contexts is a crucial step. We think that in the upcoming years, Oculus – the most known VR headset – shall integrate brainwave sensors which will add to the experience of users to a great extent. Such an implementation will significantly affect our approach to designing architectural spaces. Kim, Park, and Choo (2021) found significant differences between the ratio of alpha and beta waves for subjects experiencing a VR space with varied architectural aspects. However, this type of data is only understandable by experts in the field. The validation of low-cost portable EEG headsets in accurately detecting emotions can provide more insights to the general public about their feeling and preferences of the built environment. In addition, collecting

analytics from individuals living in the same environment can provide more significant insights to designers and policymakers into ways of positive, informed interventions.

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REFERENCES

- ALPERT, M., ROSEN, A., 1990. A semantic analysis of the various ways that the terms “affect,” “emotion,” and “mood” are used. *Journal of Communication Disorder*, 23, 237±246.
- ALLEN, C., MACHLEIT, K., KLEINE, S., NOTANI, A., 2005. A place for emotion in attitude models. *J. Bus. Res.* 58, 494–499. doi: 10.1016/s0148-2963(03)00139-5
- BATSON, C. D., SHAW, L. L., OLESON, K. C., 1992. Differentiating affect, mood, and emotion. In M.S. Clarke (Ed.), *emotion* (pp. 294±326). Newbury Park, CA: Sage.
- BAGOZZI, R. P., GOPINATH, M., NYER, P. U., 1999. The role of emotions in marketing. *J. Acad. Mark. Sci.* 27, 184–206. doi: 10.1177/0092070399272005
- BELL M. A., FOX N. A., 1992. The relations between frontal brain electrical activity and cognitive development during infancy. *Child Development*. 63:1142–1163. doi: 10.1111/1467-8624.ep9301210012.
- BELL M. A., FOX N. A., 1994. Brain development over the first year of life: Relations between electroencephalographic frequency and coherence and cognitive and affective behaviors. In: Dawson G, Fischer KW, editors. *Human behavior and the developing brain*. New York: Guilford;. pp. 314–345.
- BELL M. A., 2012. psychobiological perspective on working memory performance at 8 months of age. *Child Development*.;83:251–265. doi: 10.1111/j.1467-8624.2011.01684.x.
- BELL, M. A., CUEVAS, K., 2012. Using EEG to Study Cognitive Development: Issues and Practices. *Journal of cognition and development: official journal of the Cognitive Development Society*, 13(3), 281–294. <https://doi.org/10.1080/15248372.2012.691143>
- BETTIGA, D., BIANCHI, A. M., LAMBERTI, L., NOCI, G., 2020. Consumers Emotional Responses to Functional and Hedonic Products: A Neuroscience Research. *Frontiers in Psychology*, 11. doi:10.3389/fpsyg.2020.559779
- BLANCO, JUSTIN A., ANN C. VANLEER, TAYLOR K. CALIBO, SAMARA L. FIREBAUGH., 2019. Single-Trial Cognitive Stress Classification Using Portable Wireless Electroencephalography *Sensors* 19, no. 3: 499. <https://doi.org/10.3390/s19030499>
- BLESS, H., SCHWARZ, N., 1999. Mood, its impact on cognition and behavior. In S. R. Manstead, M. Hewstone, S. T. Hogg, H. T. Reis, & G. R. Semin (Eds.), *Blackwell encyclopaedia of social psychology* (pp. 391±396). Oxford, UK: Blackwell.
- CONRAD, M., 2022 ERPs reveal an iconic relation between sublexical phonology and affective meaning, *Cognition*, 226, 105182. doi: 10.1016/j.cognition.2022.105182.
- CUEVAS K, RAJ V, BELL M. A., 2012. A frequency band analysis of two-year-olds’ memory processes. *International Journal of Psychophysiology*. -a;83:315–322. doi: 10.1016/j.ijpsycho.2011.11.009.
- CUEVAS K, BELL M. A., 2011. EEG and ECG from 5 to 10 months of age: Developmental changes in baseline activation and cognitive processing during a working memory task. *International Journal of Psychophysiology*.;80:119–128. doi: 10.1016/j.ijpsycho.2011.02.009.
- DAVID, O., OLTEAN, H., 2015. Technology use in promoting effective emotion-regulation: Applications in workplace, parenting and for children.

- DROLET, A., WILLIAMS, P., LAU-GESK, L., 2007. Age-related differences in responses to affective vs. rational ads for hedonic vs. utilitarian products. *Mark. Lett.* 18, 211–221. doi: 10.1007/s11002-007-9016-z
- EKMAN, P., FRIESEN, W. V., 1976. Measuring facial movement. *Environmental Psychology & Nonverbal Behavior*, 1(1), 56–75. <https://doi.org/10.1007/BF01115465>
- EKMAN, P., DAVIDSON, R. J., 1994. *The nature of emotion*. Oxford, UK: Oxford University Press.
- ELLISON, C. W., MAYNARD, E. S., 1992. *Healing for the City*. In: Grand Rapids: Zondeivan.
- ELSAMAHY, E., ABD-EL-FATTAH, R., 2018. Designing non-stressed psychological public spaces. *International Conference on Urban Health & Wellbeing*, 2617-1635
- FERNÁNDEZ-CABALLERO, A., MARTÍNEZ-RODRIGO, A., PASTOR, J. M., CASTILLO, J. C., LOZANO-MONASOR, E., LÓPEZ, M. T., FERNÁNDEZ-SOTOS, A., 2016. Smart environment architecture for emotion detection and regulation. *Journal of Biomedical Informatics*, 64, 55-73. doi:10.1016/j.jbi.2016.09.015
- GARCIA, J., M., PENICHER, V., M., LOZANO, M., D., 2017. Emotion detection: a technology review. *Proceedings of the XVIII International Conference on Human Computer Interaction*, 1-8. doi: 10.1145/3123818.3123852
- HASSENZAHN, M., 2018. The thing and I: understanding the relationship between user and product, in *Funology 2. Human–Computer Interaction Series*, eds M. Blythe and A. Monk (Cham: Springer), 301–313. doi: 10.1007/978-3-319-68213-6_19
- HAN, D., KONG, Y., HAN, J. ET AL., 2022. A survey of music emotion recognition. *Front. Comput. Sci.* 16, 166335. <https://doi.org/10.1007/s11704-021-0569-4>
- JAIN, R., BAGDARE, S., 2011. Music and consumption experience: A review. *International Journal of Retail & Distribution Management*, 39, 289-302.
- JAIN, C., SAWANT, K., KUMAR, R., 2018. Emotion Detection and Characterization using Facial Features. *3rd International Conference and Workshops on Recent Advances and Innovations in Engineering*. 1-6, doi: 10.1109/ICRAIE.2018.8710406.
- KIM, J., AND MORRIS, J., 2007. The power of affective response and cognitive structure in product-trial attitude formation. *J. Advert.* 36, 95–106. doi: 10.2753/joa0091-3367360107
- KIM, S., PARK, H., CHOO, S., 2021. Effects of Changes to Architectural Elements on Human Relaxation-Arousal Responses: Based on VR and EEG. *International journal of environmental research and public health*, 18(8), 4305. <https://doi.org/10.3390/ijerph18084305>
- KOPP, C. B., 1989. Regulation of distress and negative emotions: A developmental view. *Developmental Psychology*, 25(3), 343–354. <https://doi.org/10.1037/0012-1649.25.3.343>
- KURDI, B., LOZANO, S. & BANAJI, M. R., 2017. Introducing the Open Affective Standardized Image Set (OASIS). *Behav Res* 49, 457–470 . <https://doi.org/10.3758/s13428-016-0715-3>
- LARSEN, R. J., DIENER, E., 1992. Promises and problems with the circumplex model of emotion. In M.S. Clark (Ed.), *Review of personality and social psychology: Emotion* (Vol. 13, pp. 25-59). Newbury Park, CA: Sage.
- LIPOVAC, D., ŽITNIK, J. & BURNARD, M.D., 2022. A pilot study examining the suitability of the mental arithmetic task and single-item measures of affective states to assess affective, physiological, and attention restoration at a wooden desk. *J Wood Sci* 68, 35. <https://doi.org/10.1186/s10086-022-02042-5>
- LI, LING., 2020. Music Emotion Capture: sonifying emotions in EEG data.
- OAKES, S., NORTH, A. C., 2008. Reviewing congruity effects in the service environment musicscape. *International Journal of Service Industry Management*, 19, 63-82.

- PANKSEPP, J., 1994. Basic emotions ramify widely in the brain, yielding many concepts that cannot be distinguished unambiguously . . . yet. In P. Ekman & R. J. Davidson (Eds.), *The nature of emotion* (pp. 86±88). Oxford, UK: Oxford University Press.
- RAMIREZ, R., PALENCIA-LEFLER, M., GIRALDO, S., VAMVAKOUSIS, Z., 2015. Musical neurofeedback for treating depression in elderly people. *Frontiers in Neuroscience*, 9. doi:10.3389/fnins.2015.00354
- RHUE, L., 2018. Racial Influence on Automated Perceptions of Emotions. Available at SSRN: <https://ssrn.com/abstract=3281765> or <http://dx.doi.org/10.2139/ssrn.3281765>
- RUSSELL, J. A., 1980. A circumplex model of affect. *Journal of Personality and Social Psychology*, 39(6), 1161–1178.
- SCHREUDER, E., VAN ERP, J., TOET, A., & KALLEN, V. L., 2016. Emotional Responses to Multisensory Environmental Stimuli. *SAGE Open*, 6(1), 215824401663059. doi:10.1177/2158244016630591
- SELYE H., 1974. *Stress without distress*. Philadelphia, PA:J.B. Lippincott Co
- SELYE H., 1977. *The stress of my life: a scientist's memoirs*. Toronto: McClelland and Stewart.
- TUGADE, M. M., & FREDRICKSON, B. L., 2006. Regulation of Positive Emotions: Emotion Regulation Strategies that Promote Resilience. *Journal of Happiness Studies*, 8(3), 311-333. doi:10.1007/s10902-006-9015-4
- TURLEY, L. W., MILLIMAN, R. E., 2000. Atmospheric effects on shopping behavior: A review of the experimental evidence. *Journal of Business Research*, 49, 193-211.
- WIERZBICKA, A., 1992. Talking about emotions: Semantics, culture, and cognition. *Cognition and emotion*, 6, 285±319.
- WOLFE C. D., BELL M. A., 2004. Working memory and inhibitory control in early childhood: Contributions from physiology, temperament, and language. *Dev Psychobiol.*;44(1):68-83. doi: 10.1002/dev.10152. PMID: 14704991.