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Using Event-Related Potentials (ERP) to identify the purchase intention of a consumer for familiar brands

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Abstract: Several neurological processes are undergoing on a conscious and subconscious level every time a consumer likes or dislikes a product. There is presently significant research in Consumer Neuroscience based on consumer behaviour and understanding of these processes. In this study, we have used Electroencephalography (EEG) and Event-Related Potentials (ERP) to capture consumer responses to highly familiar product images. EEG analysed from the 27 participants was used to extract P1, N1, P300, N400 and Late Posterior components. The analysis showed that the early ERP components viz., P1, N1 and P300 can differentiate between consumer liking and disliking of products. In contrast, the late ERP components N400 and Late Posterior components could not differentiate in the highly familiar product category. The results indicate that after continuous exposure, consumer preference towards highly-familiar products occurs as a part of automatic, unconscious mental processes irrespective of the product properties. Further research in this direction can test for the transference of consumer preference: from a conscious mental process to a subconscious mental process due to excessive and continuous product exposure and marketing repetition. Our study demonstrates that consumer behaviour in response to highly-familiar products can be classified using early ERP components only.

Keywords: Consumer behavior; Electroencephalography (EEG); Event-related potentials (ERP); Unconscious mental processes

1.0 INTRODUCTION

Consumer responses to products depend mainly on their prior experience with them. Traditional marketing techniques have focussed on questionnaires and surveys to understand consumer perception towards a product; however, the changes in consumer neuropsychology during the exposure to marketing stimulus are challenging to understand using traditional marketing research tools. The traditional marketing techniques also possess the downside of hiding the individual opinions and perspectives of the participants since they are often influenced by group responses (Kocher et al., 2018). These downsides are overcome using neuroimaging tools (Alsharif et al., 2022), where the consumer responses are instantaneously recorded without any scope for false reporting by the focus group members. Several neuroimaging tools are being researched for their potential use in market research. (Alsharif et al., 2021a). This field of research is called Consumer Neuroscience or Neuromarketing. (Alsharif et al., 2021b)

An essential aspect of product perception is consumer familiarity with the product. An unfamiliar product leads to a novel response from the consumer, and the effects cannot be observed over successive exposure to the product. The consumer understands a familiar product well, and the brain responses elicited are normalised as the novel factor has faded. However, once a product has established itself in the market after years of presence, consumers do not consciously respond to it. In this study, we show consumers these "highly familiar" products and use neuroimaging to identify consumer perception.

Here, we propose using Event-Related Potentials (ERP) (Jiang et al., 2014; Yadava et al., 2017) as the analysis technique to identify the EEG correlates of liking and disliking a highly familiar product. We have used ERP components to determine whether a consumer perceives a product positively or negatively. We explored the early ERP components and the late ERP components. We found that only the early ERP components can differentiate between liked and disliked products in the highly-familiar category.

Neuromarketing techniques are mainly focused on identifying the effects that new products have on the consumer. It is equally important to understand the brain neurophysiology for products that are well established and have successfully triggered the "Buy Button" over several years. It is also important to identify if the neural correlates of the sub-conscious consumer perception can differentiate between Liked and Disliked products. Finally, the findings of our study can be used by existing brands for further neural analysis.

1.1 Conceptual framework

Product advertising has inundated the consumer world with new and more innovative product placements being introduced regularly. These products appeal to the senses making them likeable to the consumer. The term sensory marketing has been defined as marketing that engages consumer perception, judgment and behaviour (Krishna & Schwarz, 2014). Sensory marketing creates subconscious triggers to convey abstract notions of the product forming a brand personality. For example, product logos were found to help consumers create a distinction between companies and convey details in a very concentrated graphic representation (Adîr et al., 2014). A logo has many attributes and functions, with shape and colour playing a critical role in its formation. Further information on the product label also influences consumer perception (Dang & Nichols, 2022). These product logos trigger instantaneous neural responses in the consumer brain called Event-Related Potentials (ERP).

In the marketing world, brands project their offerings continuously to the consumer in the form of repeatedly appearing advertisements in visual and print media. Consumers consume the advertisements and experience the product, thus increasing the level of familiarity of the consumer with these products. Over repeated product engagements or experiences, the consumers make a consistent choice towards a product, which is to like it or dislike it. Over these successive engagements, the neural correlates to consumer response would also stabilise. Thus, the neural processes in action will differ from products/brands with limited consumer experience. These are the neural processes that interest enterprises with existing brands and products. We call it the "highly-familiar" products. Previous research also shows that the neural processes in response to stimulus changes if shown repeatedly (Bleich et al., 1996; Coll et al.,2016; Han et al., 2020). Our study focuses on consumer perception of the well-established highly-familiar product category.

Event-Related Potential can be defined as "a set of voltage changes that are consistent with a single generator site and that systematically vary in amplitude across conditions, time, individuals, and so forth and a source of systematic and reliable variability in an ERP data set" (Luck, 2005). Event-related potentials can be classified as exogenous (caused as a result of an external trigger event) or endogenous (in anticipation of a trigger or caused by a cascade of neural responses forming the neural response pathway).

The primary objective of this study is to investigate the neural correlates when a consumer likes or dislikes the product unconsciously (highly-familiar product category). Initial research in this area has associated consumer liking with decision-making and the elicitation/modulation of the P300 ERP component (Chen et al., 2009; Martin & Potts, 2009). Research has also shown an association between the consumer purchase decision and the changes in Late Positive Potential (LPP) (Shen et al., 2018).

However, recent research efforts have considered that liking and disliking a product also depends on the familiarity of the product in the consumer's mind. ERPs were separated into early and late components and were individually studied with familiarity grouping (Ozkara & Bagozzi, 2021). They aimed to investigate the effect of familiarity on consumer decision-making and found that early ERP components (before 300ms) could not differentiate between purchased and unpurchased items for unknown brands. However, for reviewed and experienced brands, the late ERP components (after 300ms) can differentiate purchased and unpurchased items. Their results suggest that both conscious and unconscious processes are involved in the purchase decision depending on the familiarity of the product. They do not study the neural correlates for highly familiar products.

Our study aims to identify ERP components that can differentiate between liked and disliked products. We show products that are familiar to the participants and that have been repeatedly shown in the market. Thus, all the products belong to the "highly-familiar" category. Consumer decisions for such products are unconscious/instantaneous due to the repeated behaviour of purchase decisions. Thus, behaviour towards highly-familiar products should activate early ERP components differently for liked and disliked items. Late ERP components are less likely to help separate the liked and disliked items in this familiarity class.

We formulated our hypothesis as follows: When products that are highly familiar to consumers are shown to them,

H1. Only Early ERP components (before 300 ms, including P300) will significantly differentiate between liked and disliked products.

H2. Only Late ERP components (after 300 ms) will significantly differentiate between liked and disliked products.

2.0 MATERIALS AND METHODS

2.1 Participants

We recruited 29 voluntary participants (26 male, 3 female, mean age ± s.d. = 21 ± 1.81 yrs) with no reported history of neurological illness to participate in the study. They were also advised to be well-rested before the day of the EEG data acquisition. After the recording session, remuneration was provided in the form of coupons. All participants provided written informed consent before participating in the experiment. All participants had normal or corrected to normal vision. They were given a detailed explanation of the experiment and their task. Two male participants did not complete the experiment as the EEG electrodes got displaced due to excessive head movement. The analysis did not include EEG and response data collected from these participants. The study was approved by the Institution Human Ethics Committee (IHEC) (approval No. IHEC 40/16-1). All the EEG data collection sessions were carried out in accordance with institutional regulations and guidelines.

2.2 Stimulus, apparatus and procedure

For this study, we created a choice task asking the participant to choose pictures they liked and the pictures they disliked. Each picture is an image of a product with its branding appearing prominently. The stimulus set contained 94 product images. The pictures were colour images within a bounded box of 10cm x 10 cm and belonged to the food, electronics and consumables segments. A sample of the pictures shown can be seen in **Figure 1(C)**. All pictures belonged to the same group without distinction based on any criterion. The pictures chosen were either seen or used by the participants. The brands used in this study have been in the domestic market for several decades and, thus are highly familiar to the participants. There were no conditions/guidelines given to the participants for picture selection. The selection process was entirely determined by prior experience with the product. Thus, it is likely that a product image liked by some may not be liked by others. To acclimatise to the task and provide quick responses, they were also asked to undergo a practice task of identifying whether a given number on the screen was even or odd.

Figure 1 shows the stimulus protocol designed for this study. A Java swing-based program was used to create the stimulus presentation for the participant. For every stimulus presented, a response needs to be given; left-click of the computer mouse represents "Like", and right-click of the computer mouse represents "Dislike".

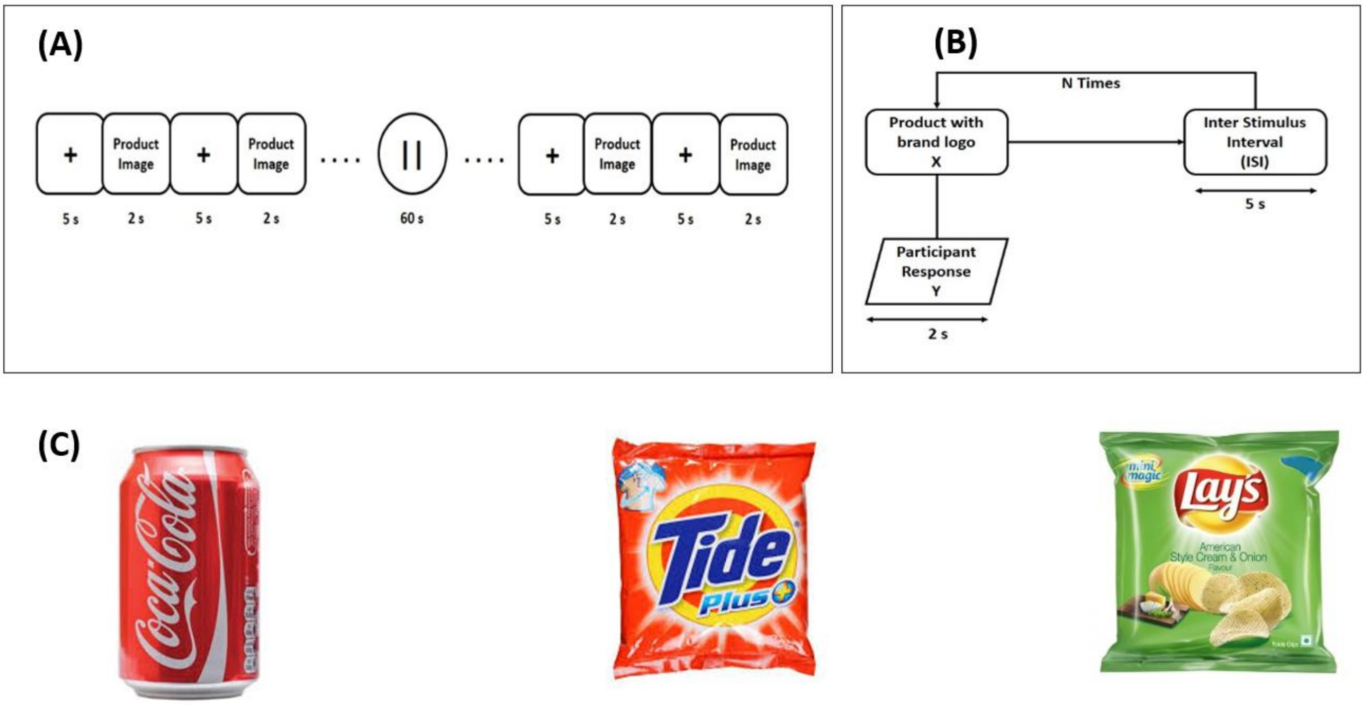

Figure 1. (A) The Stimulus Presentation diagram showing alternate fixation and products being presented. **(B)** The UI control components and the User response window **(C)** Sample product images that are shown to the participants.

In between stimuli, a fixation of 5000 ms was presented to the participant. The pictures were presented for up to 2000 ms, and the participant had to provide his preference. The image presentation stopped as soon as the response was provided. The program records the type of response and the time taken to respond. The counterbalance for the response type is not programmed in the experimental design. Events are sent to the EEG recording system for easy time locking and segmentation for ERP analysis at every stimulus change.

A 32-channel electrolyte-based EEG acquisition system from Electrical Geodesics Inc. was used to collect EEG data while conducting the task. All electrodes are placed according to the 10-20 International electrode placement standard. The stimulus was presented on a 21" LCD screen at a distance of 80 – 83 cm from the viewer and at an angle of 10 – 15 degrees below the eye line. Impedance values were below 50 kΩ (EGI specification) before the experiment started. EEG data were collected at a sampling rate of 250. The EEG data were not resampled as the sampling frequency exceeded the Nyquist frequency threshold. (Williams et al., 2021) Thus, the final sampling frequency is 250 Hz.

2.3 EEG pre-processing

EEG data files from the EGI acquisition system were imported into EEGLab (Delorme & Makeig, 2004) for initial pre-processing. EEG data were band-pass filtered between 0.1 Hz to 30 Hz. Bad EEG channels were interpolated. If the interpolation was not possible, such datasets were removed from the analysis. EEG data from two participants were found to be noisy during the experiment, and their respective session was interrupted. The EEG collected from these participants was thus not considered for further analysis. We then changed the montage for the EEG measurement into an Average Referential Montage to correlate our ERP findings with existing literature. ERPLab (Lopez-Calderon & Luck, 2014) plugin was used to assign bins and then to create bin-based epochs using the response given by the participants. All EEG segments were created with a [-200 ms, 1200 ms] segment locked to the picture presentation time. This was followed by baseline normalisation using the pre-event signal [-200 ms,0 ms] to average the EEG segment. EEG segments that were unusable due to high muscle artefacts were removed through visual inspection. EEG artefacts were then removed using Independent Component Analysis (ICA), MARA (Multiple Artifact Rejection Algorithm) (Winkler et al., 2014; Winkler et al., 2011) and visual inspection.

Several artefacts like eye blinks and smaller muscle movements, were removed through the process. Finally, the EEG data were resampled to 125, sufficient for plotting smooth ERP waveforms and quality ERP analysis. The data is ready for averaging over trials (intra-subject) and grand averages (inter-subject).

2.4 Behavioural analysis

To compare the liked and disliked products, we first assessed the responses provided by the participants. Firstly, the average response time for each of the products was measured. As described earlier, the stimulus contained only previously known products. Thus, a consumer takes minimal time to identify the product while most of the time is spent deciding whether they like or dislike the product they see. The response time for any product determines the clarity of thought about the product. Consumers spend more time liking products than disliking them, as found by (Herr & Page, 2004). Thus, we can make two inferences concerning our experimental design: (i) Participants like more products than they dislike products. (ii) The average response time for liked products is less than that for disliked products.

We conducted a paired sample t-test to compare the average response times for the two classes (Like and Dislike). Our null hypothesis (H0) is that the average response time of liked products is not significantly smaller than that of disliked products. The alternative hypothesis suggests that participants take smaller amounts of time liking the products than they dislike them. We discuss the results of this test in the results section.

Next, we compare the average number of products liked and disliked by the participants. From (Herr & Page, 2004), we estimate that there is a significant difference to be expected between products that are liked and the products that are disliked. **Table 1** shows the distribution of the participant responses.

The results showed that participants liked more products than they disliked. This aligns with previous literature (Herr & Page, 2004) about the disproportion between liked and disliked products. However, this disproportion in the choice between like and dislike does not help us identify the behaviour that determines an image being disliked.

Table 1. Participant response distribution

No of Participants = 27, Total No of Images: 94		
	Mean	Std. Dev.
Likes	52.22	9.19
Dislikes	30.15	10.56
Not Answered	11.63	9.01

2.5 ERP analysis

We analysed early and late ERP components in various regions of the brain anatomy to differentiate between products that were liked and those that were disliked. All ERP components that are described to appear around and before 300 ms were termed as early ERP components, and the ERP components appearing later were termed as late ERP components. As per the above convention, the early ERP components analysed are the P1, N1 and P300 components. The N400, Late Posterior Negative ERP and the Late Posterior Positive ERP components are considered the late ERP components.

These ERP components were chosen using previous literature that analysed these ERP components (Ozkara & Bagozzi, 2021). The EEG space was divided into 4 areas, i) Frontal region (Fp1, Fp2, Fpz, F3, F4, F7, F8, Fz), ii) Central Region (Fcz, C3, C4, Cz), iii) Parietal Temporal Region (P3, P4, Pz, T3, T4, P7, P8), iv) Parietal Occipital Region (O1, O2, Oz, P7, P8, Po9, Po10).

Each ERP component represents a specific neuronal activity and is observed in certain brain regions. The P1 component (70 – 110 ms) represents early sensory perception in response to external stimulus. The N1 or the N100 component appears as a negative peak between 130 – 200 ms after the stimulus in the frontal region. The P300 ERP component is considered endogenous and appears in the time window of 250 – 300 ms post-stimulus. This ERP component is elicited in the process of decision-making, which in our case, is the decision to like or dislike the product. The N400 ERP component, primarily elicited in the parietal regions, appears as a negative peak in the 350 – 500 ms time window. The Late Posterior components (Negativity and Positivity) appear in the 600 – 800 ms time range in the posterior regions and represent the emotional intensity of a stimulus.

All the aforementioned ERP components were computed by calculating each participant's mean amplitude of the grand average ERP and decision (Like/Dislike). A paired sample t-test was used to compare the mean amplitude of the ERP components.

3.0 RESULTS

3.1 Behavioral results

A pairwise t-test between the average response times (RT) showed that the participants took less time to like a product than dislike it. The results of the t-test and the mean RT statistics are given in **Table 1** and **Table 2**, respectively, and **Figure 2** shows the comparison of the RT's. We also ran the Shapiro-Wilk test for data normality to confirm that the results were correct. With a p-value of 0.702, the data is certainly normally distributed, as shown in **Table 3**.

The behavioural results indicate a pattern in the instantaneous responses of the participants. Larger RT's indicate longer processing/analysing time taken to evaluate the product. Earlier research has suggested that consumers take a shorter time to features of products and longer to identify dislikeable features of the products. This is confirmed by our statistical tests, as indicated by low p-values. Another explanation for the difference between RT's could be the participants' relative frequency of usage of the mouse buttons (Generally, we do more left clicks and fewer right clicks). We eliminated this potential cause by comparing the RT's collected during the practice task. We found no difference in RT's when the participants identified a number as even (left click) or odd (right click).

Additionally, (Woods et al., 2015) found that reaction times for mouse clicks are comparable when a cognitive task is introduced in the experimental design. Although we see significant differences in RT values between Like and Dislike conditions, it cannot be used as a valid marker for a consumer liking or disliking a product. This is because we cannot establish a minimum threshold for the response time beyond which a consumer dislikes a product. As seen in **Table 3**, there is considerable overlap in the RT values. Thus, disliked products cannot be distinguished from liked products just using RT values.

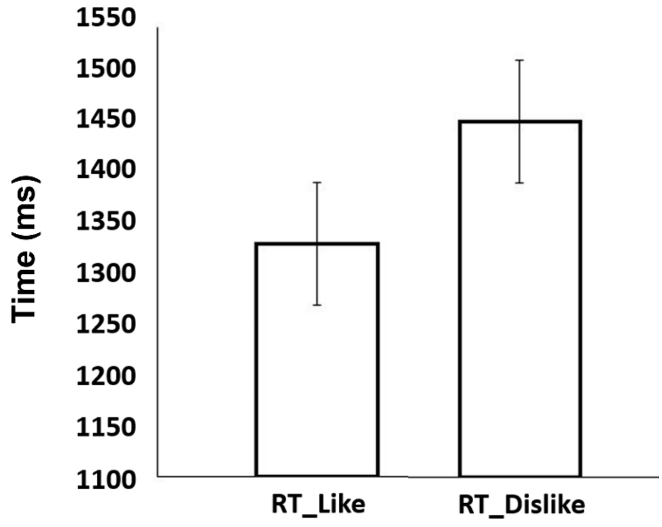

Figure 2. Like and dislike response time comparison. The mean response plots are made with a confidence interval of 95%. The error bars represent Standard Error (S.E.)

3.2 ERP results

As described in the analysis section, we divided the ERP components into the early and the late ERP components. **Table 4** shows the statistically significant ERP components that can be used to differentiate between liked and disliked product images. The table also lists the brain region where the ERP component was significant.

Table 2. Paired sample t-test between like and dislike response times

Measure 1	Measure 2	t	Df	p	Mean Difference	SE Difference
RT (Like)	RT (Dislike)	-8.251	26	< .001	-122.818	14.885

Table 3. Response Time comparison between liked and disliked images.

	N	Mean (ms)	SD	SE
RT_Like	27	1333.080	146.019	28.101
RT_Dislike	27	1455.898	169.639	32.647

Table 4. Results of the paired sample t-tests*.

ERP	Region	Liked		Disliked		df	T	p-value
		Mean	S.D.	Mean	S.D.			
P1	Frontal	0.094	0.178	-0.069	0.381	26	1.803	0.042
	Central	0.073	0.307	-0.098	0.453	26	1.672	0.050
N1	Frontal	-0.143	0.333	0.034	0.486	26	-1.713	0.049
	Central	-0.159	0.350	0.107	0.541	26	-2.007	0.028
	Parieto-Occipital	0.171	0.407	-0.057	0.607	26	1.823	0.040
P300	Parieto-Temporal	-0.006	0.172	0.101	0.257	26	-2.341	0.014
N400	Frontal	0.023	0.116	-0.029	0.100	26	1.852	0.038

* $p < 0.05$

ERP data from 27 participants were included in this study. All the liked and disliked images were grouped using the participants' responses. The number of data points is unequal because the participant determines a product's category. A product may be liked by one participant and disliked by another participant. Thus, the grouping does not consider the product itself. Grouping is only done based on participant responses. Although most participants were male, there is no corresponding bias in the ERP results due to this. (Choi et al., 2017) found that product categories can be linked to gender only if the categories are targeted towards a specific gender. Gender-neutral products do not have gender-specific neural responses. Since the products we show in our study are not targeted towards a specific gender, the ERP results can be generalised to both genders.

We conducted a paired sample t-test to compare the ERP components that represented liked and disliked products. We computed the Shapiro Wilk test for all variables to ensure that the data is normally distributed. The regions where the ERP mean amplitudes did not follow normal distribution were not considered for the t-tests. The statistical tests were done using JASP software (JASP & JASP Team, 2019).

The results indicate the important role of early ERP components in differentiating between the neural mechanism of Liking and Disliking a product. All early ERP components can be used in distinguishing between the two ERP classes. The Frontal and Central P1 ERP show higher mean amplitude for the Like class than the Dislike class. The Frontal and Central N1 ERP shows a higher negative mean amplitude for the Like class than the Dislike class. However, the Parieto-Occipital N1 ERP shows a lower negative mean amplitude for the Like class than the Dislike class. The Parieto-Temporal P300 component has a lower mean amplitude for the Like class than the Dislike class. Finally, the Frontal N400 ERP has a higher mean amplitude for the Like class than the Dislike class. The related grand average waveforms are shown in **Figure 3**. The time windows for the ERP components are highlighted in the figures. In addition, average scalp topographies for the specific time windows are also given in **Figure 4**, corresponding to P100, N100 and P300 ERP components. Of the ERP components that can distinguish between Like and Dislike conditions with statistical significance, the Parieto-Occipital N1 and the Parieto-Temporal P300 components need further explanation. For the P300 component, it is the Dislike condition elicits the P300 component. This has a similarity to the P300 signals seen in the oddball paradigm. More products are liked than disliked in the case of highly familiar products as the products have already stood the test of time and established market presence for an extended period. Thus, a disliked product is expected to elicit a P300 ERP. In the case of the Parieto-Occipital N1, a positive peak is observed in the time interval for the Like condition and the same is missing for the Dislike condition. Using existing

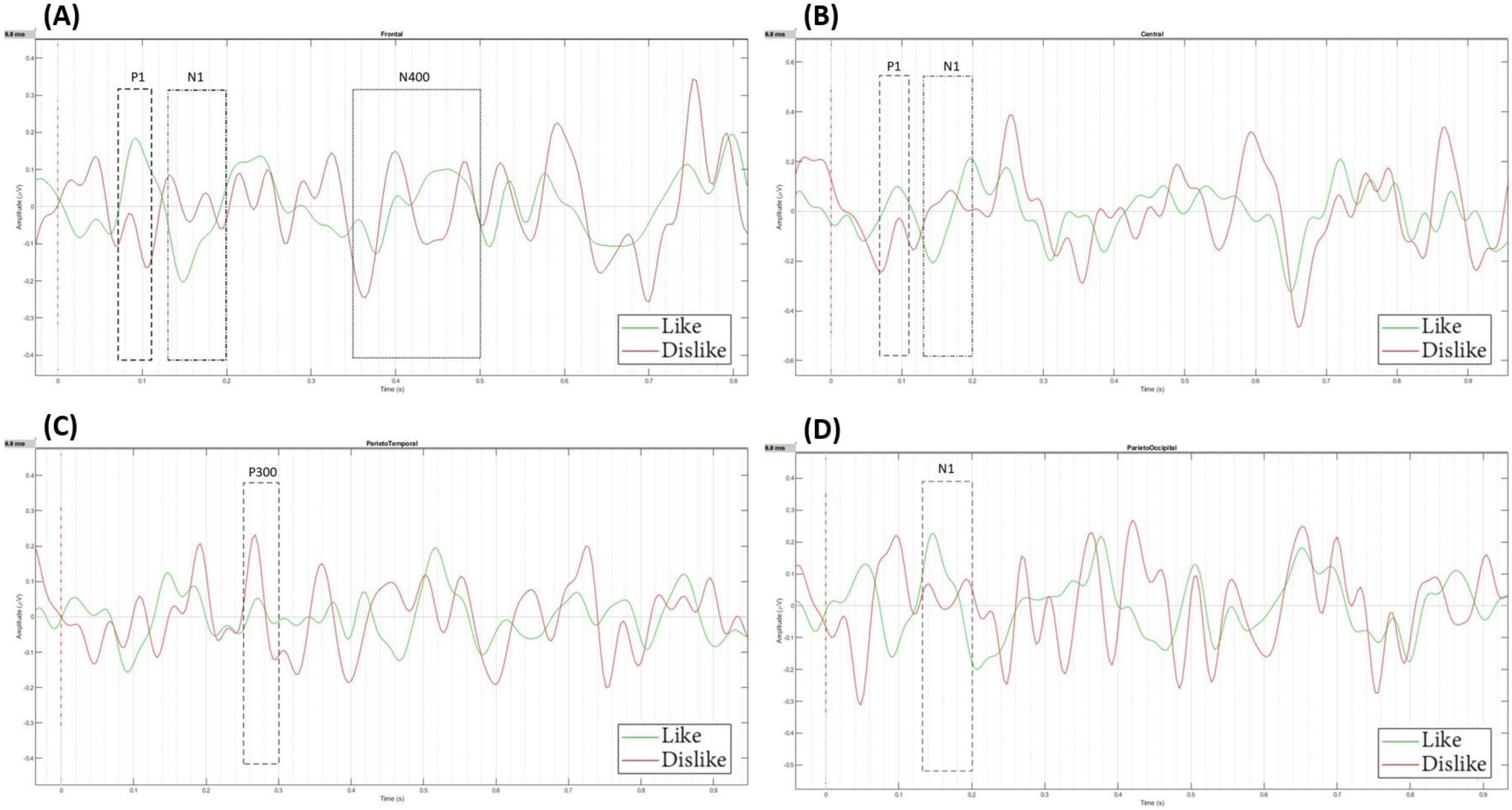

Figure 3. Grand average event-related potential waveforms at the **(A)** frontal, **(B)** central, **(C)** parieto-temporal and **(D)** parieto-occipital brain sites. Green lines: Liked products, Red lines: Disliked Products. Dashed box areas indicate the significantly differentiated time windows.

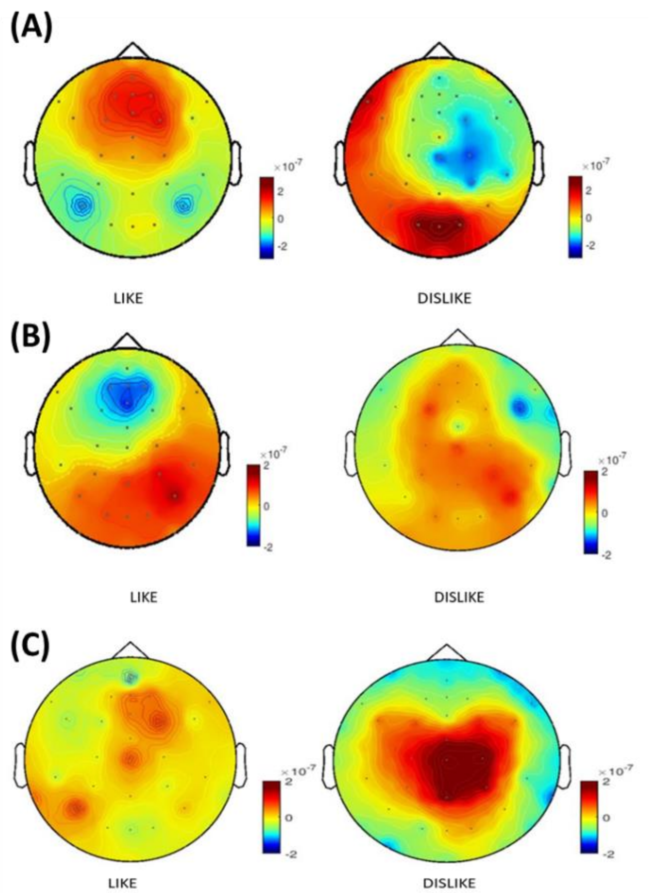

Figure 4. Average Brain topography for the time window (A) between 70 ms – 110 ms for the P1 ERP component, (B) between 130 ms – 200 ms for the N1 ERP component and (C) 250 ms – 300 ms for the P300 ERP component. The bar for the topographic map ranges from -0.2 µV to +0.2 µV.

literature (Hillyard & Anllo-Vento, 1998), we know that these are visual ERP components that appear due to the attributes of the images shown. It is a separate research field where the physical attributes of products are being analysed to identify what separates a Liked product from a Disliked product.

Pairwise t-tests on other brain regions and the late ERP components (except frontal N400) did not provide any statistical significance (available in the appendix) to differentiate liked and disliked products. Thus, we conclude that there is complete support for H1 but only partial support for H2.

4.0 DISCUSSION

Presently, one of the key research areas in consumer neuroscience is distinguishing between liked and disliked products using the neurophysiological data from the consumer. The proposed work is an addition to several such existing techniques. Unlike other studies that show marketing stimuli not encountered frequently by the consumer, we show product images repeatedly experienced by consumers and for which consumers already have an unconscious preference. We divided the ERP components into early and late neural processes and attempted to distinguish between liked and disliked products using these ERPs.

Previous research done by (Ozkara & Bagozzi, 2021) observed that unknown brands did not evoke complex processing in the consumer. Thus early ERP components were able to differentiate between purchased and non-purchased products. However, a reviewed or experienced product evoked decision-making neural activity, and only the late ERP components could differentiate between purchased and non-purchased products.

In our study, the stimulus contains products regularly encountered and repeatedly experienced by the consumer and thus already have a consumer preference attached to it. Therefore, being familiar with the product, user preferences are pre-determined over several engagements/experiences. Thus, no conscious neural processes are activated in showing these products to the consumer. Instead, early neural processes are activated, which can differentiate between liked and disliked products.

Insights from this study point towards a specific consumer behaviour that has not been extensively studied in the consumer neuroscience domain. How a brand can create an impression on the consumer psyche and what kind of neural processes are behind it are still questions that research is trying to answer. There is also relatively little literature that studies the change in neural processes due to continuous exposure to the same products over prolonged periods.

Our study found that early ERP components differentiate between liked and disliked products when the products are well-experienced by the consumer. The same ERP components can differentiate between liked and disliked products when the products are also unknown to the consumer. However, the late ERP components can differentiate between liked and disliked products when the products are reviewed or experienced. Thus, for consumer neuroscience research, familiarity should consist of 4 classes viz, unknown (never experienced the product), reviewed (reading or listening to others' experiences), experienced (experience the product once), regular experience (highly familiar) (several experiences/uses of the product). Further research in this area will be valuable to companies with existing brands and products.

Neuromarketing applications are mainly focused on improving attributes of a new product where significant scope exists for improving the product itself. Since existing brands do not see the need to change the product attributes, they seldom recruit neuromarketing tools for their existing well-established products. However, every new generation needs to be introduced to the product in a new way, and products that were loved by one generation may get ignored by the next. Hence, the neuromarketing study of highly familiar brands is equally important. Through this study, we have taken a small step in this direction. Finally, the study aims at understanding consumer perception in the highly familiar product category, which is what each product strives to achieve. Similar studies can help identify if a product belongs to a highly-familiar category.

Supplementary Materials: The results of the t-tests, which were statistically insignificant, are presented in **Table S1**.

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Author Contributions: V.B. conceived the experiment and the study; M.J and V. B. designed the experiment; M.J. performed the data collection, M. J. and V.B. analysed the data, V.B. provided the hardware/infrastructure for data collection; M.J., K. S. and V.B. wrote the paper.

Conflicts of Interest: No conflicts of interest.

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