# Ergonomics and aesthetics of seats based on users' preferences: Neuroergonomics and EEG approach


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## Abstract

Industrial designers prioritize the aesthetics of their products, drawing upon their visual training and past experiences to align with consumer preferences and evoke specific user emotions. Ergonomists, conversely, emphasize factors like safety, productivity, ease of use, and comfort in human-machine interactions, often sidelining aesthetic considerations. This study explores how the appearance of office furniture influences user perceptions of ergonomically-related comfort. We employed a method that evaluates the aesthetic indicators of Nilper chairs using brain wave mapping and measurements from an Electroencephalography (EEG) device. In a controlled lab experiment, forty participants were exposed to images of products, categorized as top sellers and low sellers. Our findings indicate that products with lower sales elicit narrower ranges of N100, N200, and P300 brain wave activity. This underscores the impact of design aesthetics on attention and product choice. Furthermore, our results suggest the potential of neuro-aesthetic evaluation methods to gauge product preference even before market release.



**Keywords:** Ergonomics, Aesthetics, Electroencephalography, Neuromarketing, Neuroergonomics


## 1.Introduction

In the 21st century, the significance of aesthetics and product appearance in system design will rise due to advancements in manufacturing technologies and complex societies and markets (Chew et al., 2016). Users' positive brain reactions can influence their product choice, suggesting manufacturers should prioritize intellectual quality and aesthetics over dependability and physical quality for market success (Liu, 2003). Academics are focusing on quantifying visual aesthetics to improve design efficiency in shape- or color-matching activities (Lu & Hsiao, 2022). Product design can help businesses differentiate their offerings and increase revenue (Ahmed & Rashid, 2021; Belboula et al., 2018; Wu et al., 2020). Product design significantly impacts consumer perception by enhancing emotional value, expressing brand personality, increasing pleasure, and attracting senses through visual appeal (Althuizen, 2021; Hemonnet-Goujot & Valette-Florence, 2022). Design firms IDEO and Alessi, for instance, use design-based innovation and product design thinking to gain comprehensive customer insights (Gilal et al., 2018). Innovation in new products can be achieved through the market pull, technology push, or design-driven approaches, with market pull focusing on customer demands and technology push driving advancements (Liberman-Pincu & Bitan, 2021). Professionals view design as a verb to address customer issues with products (Sameti et al., 2022), aiming to provide high-quality, psychologically satisfying goods that are suitable for human usage(X. Wang, 2022). Research on product design's impact on customer reactions is crucial for marketers and designers (Pleyers, 2021). The brain is a system made up of millions of thousands of neurons that is made to perceive and react to external stimuli in a very sophisticated and highly nonlinear manner (Marmolejo-Ramos et al., 2023). EEG is a temporally precise, non-invasive testing technique (Mizokuchi et al., 2023), its signals may be used to decipher emotions since they include a wealth of information about emotions (Ju et al., 2023). Cognitive function may be viewed as the brief sequential flipping between several metastable states that emerge on the neuronal, micro-network, and large-scale functional network levels of the brain (Rabinovich et al., 2023). Numerous studies have looked at the creation of non-invasive EEG-based brain-computer interfaces recently from the perspective of designing both paradigms and algorithms for extracting characteristics from EEG data (Martín-Chinea et al., 2023). Although it can experience artifacts connected to the skull or scalp, EEG is helpful since it is comparatively non-invasive and has an excellent temporal resolution (MahdiNejad et al., 2021). The synchronized activity of sizable groups of neurons is reflected in brain rhythms, which are substantial oscillations in neuronal activity that may be seen using scalp EEG and local field potential recordings (Ursino et al., 2023).

Undoubtedly one of the prominent product characteristics is ergonomics, especially about duty products, tools, seats, and so on. According to the importance of aesthetics and ergonomics, in this study, the mentioned factors were considered in seats. In this regard, one of the very well-known chair companies in Iran was selected to evaluate some of these products, in terms of aesthetics and ergonomics.

## 1.1 Ergonomics and aesthetic in product design

Human capabilities and limits have been studied since the 1940s, with significance recognized in the 1980s. Product design studies focus on human-technology interactions (Honglun et al., 2007), emotional appeal, aesthetics, and lifestyle, influencing market development(Suri & Marsh, 2000). Ergonomics concerns human beings, customer satisfaction, productivity and sustainability (NAEINI et al., 2023), with an awareness of interactions among humans and other aspects of a system (Eilouti, 2023; Kortum, 2024). Customers value ergonomically designed products that offer comfort and enjoyment, with aesthetics influencing usability (Zhang et al., 2014). Design beauty attracts customers, while ergonomic principles are crucial for designing products compatible with human components, leading to efficiency and lower costs (Sagot et al., 2003). Human-centered product design, particularly in Design for Manufacturing (DFM) and Design for Assembly (DFA), is gaining significant interest in academia and industry due to the need to address ergonomic issues early on (Kuo & Chu, 2005; Sun et al., 2018). Adapting to anthropometric variations can be challenging (Kuber & Rashedi, 2023), but poorly designed products can cause pain and health issues, impacting society financially (Sadeghi Naeini et al., 2023). Emphasizing ergonomics can differentiate products and give businesses a competitive edge (Jeang et al., 2018). Ergonomics combines human needs and product functions (Wu et al., 2020), focusing on people-oriented optimization and interaction (X. Wang, 2022). HFE professionals use a human-centered approach (Xu, 2014), to design ergonomic solutions for household products, focusing on usefulness, aesthetics, and symbolism in a three-dimensional construct (Bettels & Wiedmann, 2019). Aesthetics, influenced by individual preferences and judgments (Saleh et al., 2019), encompasses the way a product feels, looks, sounds, and smells, with factors like complexity, order, curves, and balance affecting perception (Benaissa & Kobayashi, 2023). Manufacturers and designers must have a thorough awareness of the user's perception in various usage scenarios (Buker et al., 2022). Ergonomics and aesthetics are interconnected in product design, often conflicting. For example, tool design prioritizes performance and safety over aesthetics, despite sales. Not every product can meet all ergonomic and aesthetic needs, and designers must prioritize practicality over aesthetics to ensure a positive user experience (Jiao-Jiao et al., 2014). Product design has gained attention due to the shifting consumer decision-making from price-centric to design-oriented (Sabir, 2020).

## 1.2 Neurasthenic assessment

Certain physiological indicators mirroring human thought patterns are connected to the evolving nature of aesthetic appreciation. Techniques that gather individuals' physiological information in tandem with their emotional reactions can offer immediate insights into a sequence of responses (Ding et al., 2017). Event-Related Potentials (ERPs) are used to explore the flow of visual evaluation. ERP is short for Event-Related Potential and means event-related potential. ERPs are a series of skin-recordable brain waves that occur simultaneously with the presentation of a discrete stimulus (Blackwood & Muir, 1990). Various temporal segments within Event-Related Potentials (ERPs) can illustrate human emotional responses, aiding in the clarification of cognitive function traits within the brain (Wan et al., 2021). Brain imaging, eye tracking, heart rate monitoring, blood pressure checks, and voice pitch analysis are just a few of the techniques that have been shown time and time again to be valid, useful, and trustworthy in marketing research (Y. J. Wang & Minor, 2008). Human perception is an unconscious process that is challenging for the perceiver to articulate verbally even with logical reasoning. Therefore, the application of brain approaches can assist researchers in examining human perception and serve as a supplement to the conventional subjective reporting method in determining preferences for the visually appealing aspects of furniture. Certain parts of the ERP can accurately represent early sensory processing (de Tommaso et al., 2008).

The N100, for instance, is associated with physical characteristics that are identified early in processing and are sensitive to stimulus practicality and appeal. It peaks at around 80–120 ms and is dispersed throughout the frontal or parietal lobe (Righi et al., 2014). The influence of a stimulus on visual attention is represented by the N100 component located in the frontal brain, whereas the effect of a stimulus on recognition processes is indicated by the N100 component found in the parietal lobe (Vogel & Luck, 2000). Thus, elements like color, shape, and gender can have an impact on how well people pay attention to and assimilate visual information (Guo et al., 2018). Emotional preferences for a product's appearance may produce minor N100 amplitudes in frontal and central brain regions. Thus, we suggested that low-design cosmetic goods may elicit significant N100 amplitudes in the frontal and central lobes. The P200 is an early positive ERP component that peaks 200–300 ms after the commencement of the stimulus. Research has demonstrated that images or phrases that convey threats can cause increases in the P200 amplitude (Correll et al., 2006). Scholars cannot agree on whether big or small P200 amplitude is driven by outstanding design aesthetics, though they all agree that P200 amplitude reflects early automatic emotional processing (Ma et al., 2015). Many studies of semantic conflict related to nonverbal stimuli that use elements like pictures, traffic signs, and mathematical symbols have shown that the N400 component, which peaks between 300 and 400 seconds, is sensitive to semantic incongruity (Barrett & Rugg, 1990; Hou & Lu, 2018). Research reveals that sentences with different semantic meanings might cause greater N400 amplitudes. When animal names are used with vehicle pictures, for instance, the N400 amplitude is higher than when suitable vehicle names are used (Ma et al., 2015). Similarly, a high N400 amplitude is elicited by semantically incongruent pairings of traffic signs and words (Hou & Lu, 2018). Regardless of the stimulus's circumstances, the N400 amplitude is often a suitable metric for identifying semantic incongruity or discord. Furthermore, earlier research has shown a connection between visual perception and the 200–400 ms temporal range (de Tommaso et al., 2008; Handy et al., 2010; Li et al., 2015), and reflects early sensory processing. Furthermore, the visual ERP N200 (peaking in the 200–350 ms time window) reflects beauty perception and the P300 reflects stimulus information such that greater attention leads to the generation of larger P3 waves.

## 2.Method

The present study was conducted with the aim of investigating the characteristics of office furniture and ergonomic-based comfort. For this purpose, a number of photos of furniture were taken into account, and by editing the photos, various design components such as color were tried not to interfere, and only the appearance of the furniture was checked in terms of visual features, however, considering the gathered data from the employer, all of the seats were categorized into four branches “Low-selling sofas, High-selling sofas, low-selling office chairs, high-selling office chairs. Eight photos were prepared, which are shown in Table 1 below.

Table (1): Case sample photos

| Picture 1_ Best-selling sofa | Picture 2_ Best-selling sofa |
|---|---|
|  |  |
| Picture 3 low-selling sofas | Picture 4 low-selling sofas |
|  |  |
| Picture 5 - low selling office chair | Picture 6_ Best-selling office chair |

| | |
|---|---|
|  |  |
| Picture 7_ Best-selling office chair | Picture 8_ Low selling office chair |
|  |  |

To examine the opinion of the participants while using psychophysical questioning methods, using the Emotiv Epoc + wireless system including 14 channels named F4, F8, FC6, T8, P8, O2, O1, P7, T7, FC5, F3, F7 and AF3 and electrodes The reference common mode sensor (CMS) and Driven Right Leg (DRL), which are placed at the P3 and P4 positions and above the ears, respectively, recorded the participants' brain waves (EEG). Each channel is associated with a specific functional area in the brain. Table 2 details each EEG channel and the functional brain region associated with it (Boucha et al., 2017).

Table (2): Emotiv EPOC++ channels and related brain functions

| | |
|---|---|
| AF3: Attention | O2: Visual processing |
| F7: Verbal expression | P8: Emotional: understanding, motivation |
| F3: Motor planning | T8: Emotional memory |
| FC5: Right body controller | FC6: Left body controller |
| T7: Verbal memory | F4: Motor planning for left upper |
| P7: Verbal understanding | F8: Emotional expression (anger, happy) |
| O1: Visual processing | AF4: Judgement |

The registration system, the number of electrodes and their location on the head surface are shown in Figure 1.

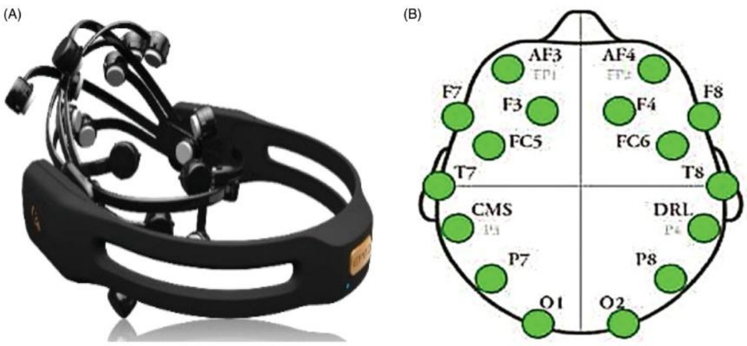


Figure (1): Neuroheadset. (Fouad, 2021).

Out of the 40 individuals who were chosen to take part in the experiment, only 31 met the qualifying requirements, which included abstaining from psychiatric drug use and ingesting coffee. The participants were then given a task that involved images, as seen in Figure 2.

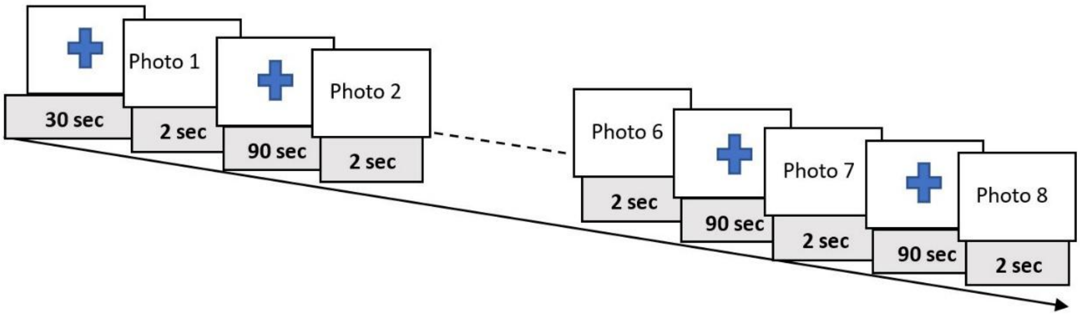


Figure (2): Task display order

In this study, participants observed photos of various chair samples, including two sets of high- and low-selling items, while sitting in front of a screen and having their brain waves simultaneously recorded. These observations are considered as external stimuli, the input of the nervous response checking system. In general, there are three methods that can measure those things that affect the minds of the audience using brain scans. In each of these three methods, after installing the sensors on the skin, the stimulus, i.e. the product or what is related to the product, is placed in front of the person (figure 3), and then the activities are monitored.

Figure (3): Steps to prepare a person for testing with an EEG device

## 3. Results

**ERP result**

The salt pads of each electrode were moistened with a saline solution. The green circles indicated that the impedance level of each electrode reached the required level for the software. The data was analyzed using the EEGLAB toolbox in MATLAB 2020a. The sampling rate of the Emotiv headset was 128 Hz. Various factors such as blinking, heartbeats, involuntary body movements, or facial muscles can create artifacts in EEG signals. Therefore, preprocessing was performed to remove these artifacts. First, the raw EEG data from 14 channels were filtered with a high-pass filter of 0.5 Hz and a low-pass filter of 40 Hz. Subpar data, such as head motions, was then manually eliminated. Subsequently, an Independent Component Analysis (ICA) was performed on the data. Additionally, the INTERPOLATE technique was used to fix problematic channels. After preprocessing, waves from 200 milliseconds before the start of each stimulus to 800 milliseconds after the start of each stimulus were isolated and analyzed using the ERPLAB toolbox. ERPs were separately averaged for each subject and each stimulus for further analysis. In this study, time windows N100, N200, P200, P300, and P400 were examined based on previous literature. Figure (4) shows the average brain topography results on channels F8, F4, AF4, T7, and O2 for extracting components N100, N200, P200, P300, and P400 for low and high-selling groups of sofas and chairs. The frontal regions in all groups showed more activity for high-selling office chairs compared to low-selling ones, while the occipital region was more active for low-selling office chairs.

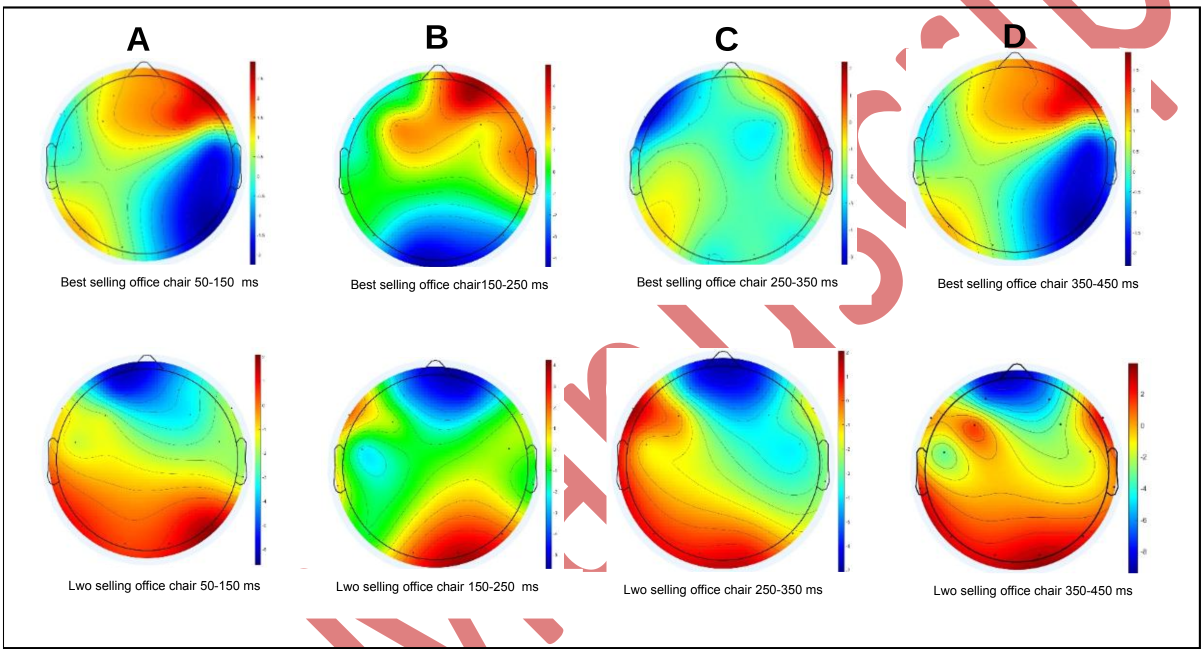


Figure (4) average Brain topography for the time window (A) between 50 ms –150 ms for the N100 ERP component, (B) between 150 ms –250 ms for the N2 ERP componentand (C) 250 ms –350 ms for the P300 ERP component and (D) 350 ms –450 ms for the P400 ERP component. The figure (5) also displays grand average waveforms for 4 groups of sofas and low and high selling office chairs for different time windows in channels F8, F4, AF4, T7, and O2. The time windows for each channel are indicated in the figure.

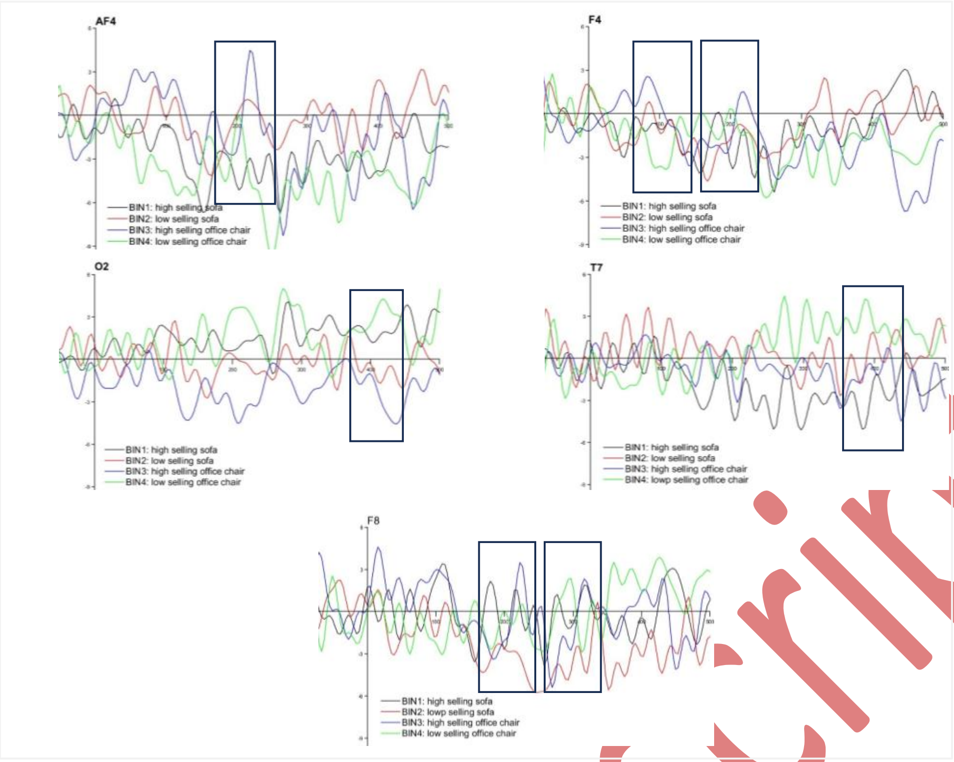


Figure (5) Grand averaged ERPs from the 4 groups for the low and best-selling stimuli (sofa & office chair) at F8,F4,AF4,T7 and O2 .

**Statistical Analysis:**

The Kolmogorov-Smirnov test was used to assess the data's assumed normalcy. Subsequently, repeated measures analysis of variance (ANOVA) was performed on the data that satisfied the normalcy requirements. When the ANOVA produced significant findings, the Bonferroni post-hoc test was employed to compare the groups. The results of the Bonferroni post-hoc test for intergroup comparisons were significant ($p<0.05$) and are presented in Table (2). (It is worth noting that the groups of low-selling sofas, high-selling sofas, low-selling office chairs, and high-selling office chairs were each considered as a group).

Table (2). The results of the Bonferroni post-hoc test for significant between-group comparisons at different scalp locations in the time interval from 200 milliseconds (μV) before the onset of the stimulus to 800 milliseconds(μV) after the onset of the stimulus. Statistical analysis in the time window of 50 to 150 milliseconds for N100, 150 - 250 ms for N200, 250 - 350 ms for P300, and 350 - 450 ms for P400 were significant. The peak N100 in F4, peak N200 in AF4, and peak P300 in F8 in the frontal regions had an effect, but no significant effect was observed in the other channels. Also, the peak P400 in T7 and O2 was significant, indicating the participants' sustained attention and visual processing.

Table (3): The results of Benferroni's post hoc test for significant inter-group comparisons in different head locations in the time interval of 200 milliseconds ($\mu$V) before the start of the stimulus to 800 milliseconds ($\mu$V) after the start of the stimulus

| Channel number | Peak | A (Best selling) | B (Low selling) | The difference between A and B | standard deviation | P value |
|---|---|---|---|---|---|---|
| F8 | Average difference in 150 to 250 ms | office chair | office chair | 11.45577 | 3.883276 | 0.034297 |
| F8 | Average difference in 250 to 350 ms | sofas | office chair | 10.55703 | 2.931077 | 0.005983 |
| T7 | P400 | sofas | office chair | 20.87049 | 7.313953 | 0.043862 |
| | | office chair | office chair | 20.31249 | 6.943145 | 0.036518 |
| F4 | N100 | office chair | office chair | 22.65626 | 6.757844 | 0.01185 |
| AF4 | N200 | office chair | office chair | 19.30803 | 6.77706 | 0.044363 |
| F4 | N200 | office chair | office chair | 22.65626 | 6.757844 | 0.01185 |
| F8 | P300 | sofas | office chair | 9.891057 | 3.10519 | 0.018553 |
| O2 | P400 | office chair | office chair | 9.821171 | 2.924415 | 0.011667 |

## 4.Discussion

The purpose of this study was to use the ERP approach to ascertain the impact of design aesthetics. Particularly, the N100, N200, P300, and N400 amplitudes were evaluated in order to determine the impact of design aesthetics on attention, emotions, and assessments of the product's value. Numerous academics have looked at the connection between brain activity and the sense of beauty. Zeki (2001) discovered in her research that neurophysiology may be used to investigate the connection between the brain and art. According to studies on design aesthetics (Paradiso et al., 1999), the insula, the bilaterally, and the subcallosal cingulate gyrus are among the brain areas implicated in aesthetic judgment. These regions are also linked to the processing of rewards and emotional assessment. The N200, P200, and P300 components may be boosted by emotionally stimulating or pleasurable stimuli, according to research using ERPs to assess product visual attractiveness (Guo et al., 2016). Additionally, consumers are surrounded by a variety of modern objects with comparable features and attributes. A product's first impression on a consumer is significantly influenced by its aesthetic user (Diefenbach & Hassenzahl, 2011). Users only consider a product's pricing when it captures their interest or stirs up strong feelings in them (Norman, 2004). According to a hierarchical approach to aesthetic perception, humans may classify an object's aesthetic level by pattern recognition using visual clues without recognizing all of its elements (Berlyne, 1973). For instance, a customer's first impression of a product could lead them to believe that it is attractive or neutral. The idea that "beautiful is good" associates beauty with excellence. The inner cognitive appraisal that customers desire of a product is represented by perceived quality (Orth & De Marchi, 2007). According to Hekkert et al. (2003), a beautiful shape can increase a consumer's awareness of a product's utility and usage. However, individuals assume quality or price based on extrinsic signals when it is challenging to assess a product's quality, which is frequently the case (Mumcu & Kimzan, 2015; Orth & De Marchi, 2007). Considering the increase of N100 when viewing the best-selling office chair compared to the low-selling office chair, it can be concluded that emotional experiences such as the experience of brightness, color and size are higher than the best-selling office chair. This occurrence could be explained by the fact that when participants made their decision, they instinctively identified the product's look. Our findings are in agreement with those of Guo et al (2018). Additionally, (Ding et al., 2017) employed ERP to study how people judge the aesthetic quality of smartphones, and they discovered that neutral pictures generated a bigger N100 amplitude than either liked or disliked photos. The result of our study shows that attention and better emotional experience were more for the best-selling office chair than the best-selling sofa, but this ratio was not significant enough to show importance. Considering the increase of N200 when viewing the high-selling office chair compared to the low-selling office chair, it is clear that attention, visual processing and aesthetic perception were higher for the high-selling office chair than the low-selling office chair. This issue is also true for high-selling and low-selling sofas, but the difference has not been significant. And these changes happened in the frontal region, which is responsible for processing decisions, especially about liking or disliking. Also, the increase in the p300 range, according to the articles, can indicate the aesthetic quality of artistic shapes among geometric shapes (de Tommaso et al., 2008), which according to the results, it can be stated that the visual aesthetic difference to the best-selling sofa compared to the chair Low-selling office is significant. Considering that in the present study, the N400 amplitude did not have a significant difference between the groups of products, there was no semantic conflict between the groups. The final classification of data is compiled in expert meetings and brainstorming with the help of weighting methods, quantified and the priorities of reforms and design changes. Significant disparities in ERP data between high-design aesthetic and low-design aesthetic items at the same price range imply that individuals judge things based on certain aesthetic experiences, such as perceived attention and emotional arousal.

## 5. conclusion

In conclusion, the advent of advanced technologies like EEG in market research marks a shift beyond traditional methods, unlocking deeper insights into unconscious consumer responses. This neuromarketing approach empowers companies to craft products that resonate more profoundly with hidden consumer needs, significantly enhancing market competitiveness. Central to this is the role of aesthetic design in product development. Design elements directly influence purchasing decisions, attention, and emotional engagement, thereby elevating the perceived value of a product. Utilizing approaches like the ERP method allows for an in-depth understanding of the cognitive processes involved in aesthetic perception. However, this study acknowledges certain unexplored territories in design aesthetics, such as the impact of symmetry and complexity, suggesting avenues for future research. By harmonizing scientific insights with nuanced consumer needs, companies have the opportunity to innovate, creating products that not only meet functional expectations but also captivate consumers on an emotional level.

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