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EMOTIONAL IMPACT OF FAST-FOOD ADVERTISEMENTS IN THE CITY OF MADRID
Real images vs. images generated by artificial intelligence. Neurophysiological evaluation using electroencephalogram (EEG)

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ABSTRACT

This study examines young consumers' brain activity when viewing fast-food advertisements with real versus AI-generated images, using electroencephalography (EEG). Findings reveal a dual processing pathway: AI-generated images predominantly activate the right orbitofrontal cortex and anterior cingulate, linked to rapid attention and aesthetic evaluation, while real images recruit a broader network including the right insula, temporal, and occipital regions, associated with sensory memory and interoception. These results suggest that visual authenticity modulates emotional and attentional responses differently, shaping the persuasive effectiveness of advertisements. The study highlights EEG's value in neuromarketing and raises ethical and practical implications regarding the use of AI in food advertising.

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1. Introduction

Images of processed foods (also known as fast food) generated by artificial intelligence (AI), despite their realistic appearance, elicit different emotional responses compared to real photographs, especially during the initial stages of perceptual processing, as evidenced by the brain reaction found in the evoked potentials resulting from the electroencephalogram (EEG) in our experiment. This approach offers a relevant contribution to the field of contemporary neuromarketing by exploring how AI technologies, in visual generation, influence the emotional and attentional experience of fast-food consumers from the earliest stages of perception.

Food is a fundamental element for human survival. According to cognitive neuroscience, when observing any element that appears edible (even if it is only a visual representation, such as in a photograph in an advertisement or on a digital screen), the brain almost instantly evaluates its possible caloric density (Sawada et al., 2019), and based on this, it automatically directs greater visual attention towards the food that appears to have the highest energy value within the scene. A detailed review can be found in Spence et al. (2022).

From a marketing and advertising perspective, capturing consumer attention has become an increasingly complex task. Constant exposure to advertising stimuli has triggered an adaptive response in users, known as banner blindness, which significantly reduces the effectiveness of digital advertisements (Gu et al., 2024). Added to this visual saturation is a notable decline in brand loyalty: today, purchasing decisions tend to be based more on price and convenience than on emotional attachment, due to the abundance of offers and products available (Ratta et al., 2024). These phenomena may be reinforced by the current decline of truth through deepfakes, which offer new forms of symbolic manipulation where the line between the real and the artificial or digitally created becomes blurred, potentially causing a negative commercial impact on both individual and collective decision-making. Recent studies warn that the mass dissemination of deepfakes can weaken public trust, fuel a culture of suspicion, and increase informational uncertainty (Vasilescu, 2023).

In this context, in a city like Madrid, where the urban environment is saturated with visual stimuli (from bus shelters and underground stations to digital screens in commercial hubs such as Gran Vía and Puerta del Sol), innovation in advertising formats has become essential to stand out from the crowd. Emerging AI-driven visual generation technologies are being used to create visually appealing content, with the aim of effectively activating the viewer's cognitive and emotional systems and thus amplifying the emotional impact of campaigns. Generative AI systems are capable of creating new content, such as images, text or video, by learning from large amounts of data. They use deep learning models that recognise complex patterns and, as a result, can produce results with a high level of realism and visual quality (Arias et al., 2024). These types of new-generation images raise questions about how the brain processes these advertising stimuli, which has sparked growing interest in the field of neuromarketing. In this vein, a study on the effect of advertising stimuli based on EEG conducted by Yen and Chiang (2021) showed that visual stimuli generated by AI algorithms (optimised to highlight persuasive attributes) cause more intense activation in brain regions associated with selective attention and emotional memory encoding.

The fast-food sector is one of the main drivers of advertising in urban spaces. These brands make intensive use of visual media in city centres, generating constant exposure that is difficult to avoid. The images used are often highly stimulating: close-ups of high-calorie products, saturated colour palettes, enhanced textures and, ultimately, compositions designed to induce immediate desire. This aesthetic seeks to automatically activate visual and emotional reward systems, especially in contexts of transit or waiting.

Various components of the EEG have been used to analyse how the brain responds to advertising stimuli. Among these, the N170 component stands out, a positive wave that appears approximately 140 to 250 milliseconds after the presentation of the stimulus and has been associated with early detection processes of relevant visual information (Golnar-Nik et al., 2019). Its modulation has been linked to the ability of the content to capture the observer's initial attention, a key aspect of analysis in highly visually competitive environments such as digital marketing and e . EEG studies have shown that stimuli related to ultra-processed foods elicit intense emotional responses and can influence consumption decisions, even in the absence of physiological hunger (Califano & Spence, 2024).

These findings confirm the value of EEG as a fundamental tool in neuromarketing, as it allows for the analysis of unconscious affective responses and attention patterns to advertising stimuli (Costa-Feito et al., 2023). In the field of advertising, the application of our experiment offers the possibility of comparing brain activation in response to real and artificially generated images, in order to identify which visual resources most effectively capture attention and arouse desire.

In this sense, the study does not aim to assess participants' ability to differentiate between AI-generated images and authentic photographs of food, but rather to examine whether these differ in terms of perceived attractiveness in a preconscious state of the stimulus perception process.

Given that it has been shown that the visual presentation of food on menus increases the likelihood of a dish being chosen (Hou et al., 2017), our research explores whether AI-generated images achieve a greater degree of emotional involvement in consumers and enhance the effect of advertisements in different types of businesses. Based on the emotional results obtained through EEG, this line of work seeks to verify whether such images can improve business performance or reduce costs in the production of visual material, innovatively integrating the tools of the brain and marketing.

Since Campbell's cans in the 1920s, but especially since the 1940s, fast-food chains have repeatedly resorted to using high-quality images based on realistic photography to promote their products. However, these images do not necessarily reflect the actual food that the end consumer receives. A team specialising in advertising is involved in their production, including a *home economist*, a professional responsible for preparing and presenting food for visual purposes.

This specialist applies technical and aesthetic principles to create visually optimised versions of the products, using ingredients or materials that are not always edible, but which allow the food to maintain its appearance during the photo shoot. These representations are designed to withstand demanding conditions (such as exposure to high-intensity spotlights) and maximise the visual appeal of the product for advertising purposes, which in extreme cases can be entirely fictitious, representing the supposedly real product with careful realism.

In this regard, it is pertinent to analyse the economic implications associated with both systems. According to Hartmann et al. (2023), in general terms, for the cost of one freelance image, around 2,500 AI-generated images can be produced with the same budget. Similarly, for the price of one stock photo purchased from an image bank, around 225 images can be generated with AI. In addition, the cost per click (CPC) is reduced by more than 25% when AI-generated images are used. Overall, the authors conclude that generative AI radically lowers the cost of visual content production and can produce exceptional advertising results.

In addition to the creative and economic potential offered by AI-generated images, it is essential to evaluate their effectiveness from a neurological and sensory perspective. EEG has established itself as an effective tool for analysing the cognitive and emotional responses generated by visual stimuli in consumers. According to Costa Feito et al. (2023), EEG allows us to identify patterns of attention, mental load and liking associated with visual content, providing an objective measurement of the communicative impact of an image. This is particularly relevant as it allows us to scientifically validate whether these visual resources elicit the desired reactions in the target audience. Thus, the neurocommunicative approach allows us to optimise advertising strategies.

1.1. Brain Dynamics in Decision-Making about Food Preferences

In primates, including humans, the orbitofrontal cortex plays a central role in representing reward value and, in particular, in the subjective satisfaction derived from sensory stimuli from sight, as well as from smell, taste and texture of food. The visual experience, while serving a primary function of food recognition, also actively contributes to the emotional experience associated with food (Rolls, 2023).

Evidence from cognitive neuroscience indicates that, when presented with food-related visual stimuli, a hungry brain (particularly when anticipating a preferred food) shows a marked increase in metabolic activity. Studies such as that by Wang et al. (2004) report an average increase of 24% in brain metabolism compared to the resting state.

It should be noted that a meta-analysis of fMRI studies in humans identified the medial insula, along with the orbitofrontal cortex and occipital complex, as key regions sensitive to external food cues (van der Laan et al., 2011). In line with this, (Simmons et al., 2013) demonstrated that both the anterior and dorsal medial insula respond to gustatory stimuli and are activated by food cues.

2. Objective

The objective of this study is to analyse how the brain activity of young consumers varies when viewing real images versus AI-generated images in fast food advertisements, in order to understand how these stimuli influence the perception of such images. Through this comparison, we seek to delve deeper into consumer psychology within the current digital marketing environment, evaluating how technological advances in AI visual generation affect the viewer's subjective experience in terms of attention, emotional response, and advertising impact.

3. Materials and Methods

3.1. Sample

Thirty-eight university students (15 males and 23 females, with a mean age of 20.1 years) from the Complutense University of Madrid participated in the study. All had a similar educational level, and no history of neurological diseases, psychiatric disorders, or substance use that could interfere with the results. The participants signed a written informed consent form, and the research was conducted in accordance with the principles of the Declaration of Helsinki. The protocol was approved by the Ethics Committee of the Complutense University of Madrid.

3.2. Experimental Task

The EEG recording task consisted of showing a six-minute video in a cinema using virtual reality glasses (Oculus Quest 2) connected to a laptop via Virtual Desktop software. This system was chosen based on studies that have shown that viewing audiovisual content in virtual environments intensifies the perceptual experience (Farokhah et al., 2023; Scatena, 2016).

The video consisted of a sequence of 100 images of unhealthy food, 50 of which were real photographs and 50 were generated using artificial intelligence with the Midjourney application. This tool was selected due to its widespread international popularity, as documented in Google Trends in 2024 (Google, 2024).

The AI-generated images were created using the prompts "image of unhealthy food". The images were generated on 17 November 2023 using version 5.2 of Midjourney (style raw). In each case, the first option was chosen, provided that it did not contain artefacts and had an equivalent dark background. Both the real and AI-generated images were presented for 500 milliseconds, interspersed with a black screen of equal duration.

The choice of the N170 component is based on its sensitivity to both the characteristics and degree of artificiality of the images and their emotional valence (Schindler et al., 2019).

3.3. Procedure

Each participant was assessed individually in a Faraday chamber to avoid electromagnetic interference. The task was performed in an armchair located one metre away from a 19-inch LCD screen with a refresh rate of 100 Hz, where the stimuli were presented. Participants were instructed to keep their eyes open, minimise blinking and avoid sudden movements during the session.

3.4. Electrophysiological Recording System

High-density EEG recordings were obtained using a 64-channel electrode cap designed by Neuroscan and connected to an ATI-Pentatek EEG system (Advantek SRL, CABA, Argentina). The data were processed using average reference after acquisition, applying a bandpass filter of 0.05 to 30 Hz and a sampling rate of 512 Hz. Electrode impedances were kept below 5 KΩ to ensure the absence of atmospheric noise interference. Electrodes placed on the mastoid bones were used as online references. Occasionally, noisy channels were replaced by linear interpolations from adjacent clean channels (Dmochowski et al., 2012). The latency of the N170 was analysed independently for each condition (real and AI-generated images) and for each participant.

3.5. Source Localisation

The N170 sources were estimated from the recordings of 62 electrodes from the 38 participants. To do this, the inverse EEG problem was solved using the Bayesian Model Averaging (Loreta) approach (MacKay, 1992; Penny et al., 2007; Trujillo-Barreto et al., 2004), while the individual models were calculated using low-resolution electromagnetic tomography (Loreta) (Pascual-Marqui et al., 1994).

The Loreta analysis was applied to a time window between -20 ms and +20 ms relative to the peak amplitude of the N170. The primary current density of the N170 was estimated for each participant and in both conditions using the procedure described.

Subsequently, statistical parametric mapping was performed with a voxel-by-voxel Hotelling's independent T-square test to identify statistically significant sources of the N170 under the condition of real and AI-generated images. The resulting probability maps were thresholded with a false error rate of $q < 0.05$ (Lage-Castellanos et al., 2010) and represented as three-dimensional activation images superimposed on the Montreal Neurological Institute average brain. Anatomical areas were identified according to the AAL atlas labels (Tzourio-Mazoyer et al., 2002), while local maxima were measured and located in the Montreal Neurological Institute coordinate system.

4. Results

Table 1. Table showing the main areas of activation in the unhealthy food condition IA

Area	X	Y	Z	Hotelling's T2
Frontal_Mid_Orbi_R	2	48	0	4.30
Frontal_Mid_Orbi_L	2	56	-10	3.2
Frontal_Sup_Medial_R	2	49	1	3.9
Anterior cingulate cortex_R	2	48	12	3.65
Cuneus_L	2	-72	27	3.58
Precuneus_R	2	-70	31	3.62
Precupeo_L	2	-68	30	3.55

Source(s): Own elaboration, 2026.

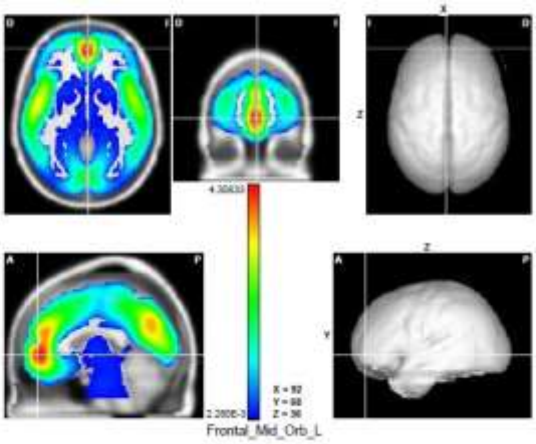
Table 2. Table showing the main areas of activation in the real unhealthy food condition

Area	X	Y	Z	Hotelling's T2
Front_Mid_Orb _L	-2	53	-4	4.17
Frontal_Mid_Orb_R	2	55	-4	4.09
Cingulum_Ant_L	-2	53	0	4.07

Frontal_Sup_Medial_L	-2	-56	-	3.88
Cuneus_L	-2	-71	30	3.66
Precuneus_L	-2	-67	29	3.60
Calcaline_L	-2	-71	22	3.78
Temporary_Sup_R	53	-7	-4	3.62
Insula_R	49	3	-4	3.41

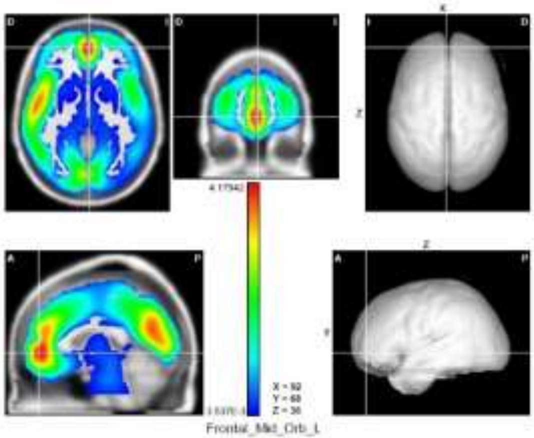
Source(s): Own elaboration, 2026.

Figure 1. Brain activity map. Neuronic AI



Source(s): Own elaboration, 2026.

Figure 2. Brain activity map. Neuronic Real



Source(s): Own elaboration, 2026.

Direct comparison between the two conditions shows a clear differential pattern in lateralisation and extension of the networks involved. In the IA images of unhealthy food, bilateral orbitofrontal activation is recorded with a clear right bias (Frontal_Mid_Orbi_R with the highest T^2=4.30 and Frontal_Mid_Orbi_L, accompanied by Frontal_Sup_Medial_R), along with right anterior cingulate (Cingulum_Anterior_R) and posterior involvement in left cuneus (Cuneus_L) and right and left precuneus (Precuneus_R and Precuneus_L). This profile suggests an emphasis on rapid assessment of reward value and attentional filtering of highly relevant visual features, enhanced by aesthetic optimisation (Kringelbach & Rolls, 2004). In contrast, real images of unhealthy food show a broader and predominantly left pattern in the medial orbitofrontal cortex (Frontal_Mid_Orb_L; T^2=4.17) and anterior cingulate (Cingulum_Ant_L), with strong left occipital involvement (Calcarine_L, Cuneus_L), left medial parietal (Precuneo_L) and, significantly, activation of the right superior temporal lobe (Temporal_Sup_R) and right insula (Insula_R). The activation of the right insula suggests a role in the integration of internal bodily signals, such as those related to physiological state or emotions, and access to sensory memories associated with previous consumption experiences (Craig, 2009), while the greater occipital-parietal extension suggests more analytical and semantically rich visual processing (Cavanna & Trimble, 2006).

The results are consistent with established neurophysiological frameworks on reward assessment and attentional prioritisation. Bilateral orbitofrontal involvement (with right-sided predominance for AI) is consistent with the encoding of subjective value and expectation of sensory pleasure in response to food stimuli (Rolls, 2023). The right anterior cingulate cortex in AI-generated images reinforces the hypothesis of motivational control aimed at prioritising relevant stimuli and facilitating response preparation (Bush et al., 2000). The greater involvement of the cuneus and precuneus in the AI condition is consistent with their role in visuospatial orientation towards relevant visual features, as well as in visual imagery and internal attention processes that favour the representation of the stimulus in working memory (Cavanna & Trimble, 2006). In the real condition, the activation of the right insula aligns with its role in the integration of visceral signals and the perception of the subjective value of food, especially when the stimulus is connected to previous taste and smell experiences (Simmons et al., 2013; van der Laan et al., 2011). The involvement of the right superior temporal lobe could be related to the evocation of memories from various senses and the integration of recurring sensory patterns linked to the act of eating (Beauchamp et al., 2004).

5. Discussion

The design of this study focuses on early perception with EEG to minimise conscious and voluntary processes and capture automatic responses from the perceptual system. This choice is relevant because components below 200 milliseconds are sensitive to early attention and affective load, respectively, and quickly discriminate the relevance of the stimulus (Golnar-Nik et al., 2019; Hudák et al., 2017). In this framework, the attentional bias towards high-energy-density foods documented by cognitive neuroscience is modulated by nutritional status, weight concerns, and especially hunger level (Sawada et al., 2019). This is central to interpreting greater orbitofrontal and cingulate focus on AI images: an internal state of greater energy need may amplify the gain of salient signals. When the organism is in a state of low need, real images (due to their greater authenticity and the sensory associations they evoke, such as smells, tastes, textures, or sounds) could more extensively activate the brain networks responsible for integrating information from different senses. Metabolic evidence that anticipation of a preferred meal significantly increases brain activity supports this line of interpretation (Wang et al., 2004).

The literature on neuromarketing suggests that enhancing persuasive features (texture, brightness, symmetry, colour saturation) increases selective attention and emotional encoding in memory (Yen & Chiang, 2021). Our pattern for the AI condition (orbitofrontal and right anterior cingulate with cuneus/precuneus support) is consistent with this rapid persuasion pathway in highly visually competitive environments such as urban settings, where repeated exposure increases the likelihood of triggering impulsive decisions (Matukin et al., 2016; Pillpe et al., 2025). This mechanism is linked to the phenomenon of "visual hunger," whereby images intensify appetite and skew portion estimation (Spence et al., 2016, 2022). For public health purposes, it is worth remembering that preferential attention to high-calorie foods is associated with an increased risk of weight gain (Meule & Platte, 2016).

Individual differences affect both the intensity and spatial distribution of brain responses, so it is essential to consider them when interpreting the data. In line with previous studies, individuals who report healthier eating habits show less reactivity to food stimuli, suggesting greater cognitive control; conversely, those who maintain less healthy habits are more susceptible to these signals (Momot et al., 2025). In a sample characterised by variability in habits and hunger levels, AI-generated images could amplify these individual differences in reward and attention networks. In contrast, real images, by evoking richer and more shared sensory memories, could attenuate some of this variability by favouring more convergent activation patterns. This point is linked to associative learning phenomena in consumers, where variables such as product appearance (e.g., perceived freshness, surface perfection, or expiry date) influence their expectations and pricing strategies, generating discount forecasts that, in turn, modify the product's valuation (Hartmann et al., 2021). In the context of advertising with AI-generated images, a “perfect” visual appearance can trigger a different set of expectations and cognitive shortcuts in the observer than those used when evaluating real products. This change in the consumer's evaluation framework can redistribute the weight they give to certain visual cues (such as colour, brightness or texture) that usually guide their judgement of quality or freshness.

It is also relevant to consider the type of food within its categorisation on a scale between healthy and ultra-processed. Some evidence suggests that AI-generated images of healthy, unprocessed foods may be less acceptable than their ultra-processed counterparts. This could be because the latter are already "socially normalised" as manipulated and stylised products, which reduces dissonance when the visual representation is artificial (van Tullen, 2023). In the case of ultra-processed foods, the boundary between traditional photographic stylisation and AI-generated images is less clear, allowing visual attributes to be optimised without perceived authenticity penalising the evaluation as much. This nuance helps to understand why, even within the "unhealthy food" category, real images activate the insula and multisensory networks more robustly: previous experiences with the real product continue to modulate interoceptive reading even at a preconscious level.

The social context and impact of current advertising messages add another layer of interpretation. The expansion of deepfakes erodes trust in audiovisual media and fuels cultures of suspicion (Vasilescu, 2023). In this climate, perceived authenticity becomes a valuable psychological resource that can favour real images in tasks that use sensory memory. Even so, from a methodological point of view, generative AI is a very valuable tool for research, as it allows for precise control of visual and emotional variables, as well as systematic manipulation of product design or message intensity, while reducing logistical difficulties and potential ethical dilemmas (Becker & Laycock, 2023).

In this context, the predictive coding framework (Friston, 2010) provides a solid theoretical basis for understanding how variations in realism and multisensory congruence affect the dynamics of brain processing. According to this model, the brain uses internal representations of previous food experiences and adjusts its responses based on the correspondence between incoming signals and its predictions. Real images, as they correspond more closely to these internal representations, tend to favour multisensory integration and the recruitment of networks associated with sensory memory and interoception or awareness of internal bodily states. In the real unhealthy food condition, the appearance of activity in the right insula fits with this idea, as it integrates signals from the body and emotions and relies on sensory memories of previous meals (Craig, 2009). If real images better match what the brain expects, the difference between expectation and visual signal decreases, the bodily relevance of the stimulus increases, and, as a result, greater insular activation and a more specific response to food content occur. Conversely, AI-generated images, although visually optimised, can introduce subtle discrepancies with these models, shifting processing to a fast-focal (lower) circuit that prioritises the immediate extraction of visual attributes and their aesthetic evaluation.

In the competitive fast-food sector, brands are constantly investing in innovative strategies for the visual representation of their products with the aim of capturing the immediate attention of consumers and standing out in an environment saturated with stimuli. In this context, the use of AI-generated food images is growing rapidly and could transform both home delivery applications and the hospitality industry itself.

This development, however, raises the need to establish clear policies regulating the use and communication of this type of content. AI's ability to produce images that are virtually indistinguishable from real photographs raises ethical questions related to potential consumer deception and highlights the importance of transparency in digital marketing (Van Esch and Stewart Black, 2021).

6. Conclusions

Beyond the technical ability to generate photorealistic images, the results of this study invite reflection on which aesthetic, symbolic and emotional aspects generate greater brain activation in consumers. In this context, the use of EEG acquires epistemological value: it allows us to explore what we understand by advertising 'effectiveness' at the neuronal level, how visual attention is configured in the brain, and which design attributes can elicit positive emotional responses or rejection. Based on these findings, the following conclusions can be drawn:

Considering the entire functional chain, the data suggest a dual circuit of persuasive effectiveness in unhealthy food advertising. In the fast-focal circuit (more evident with AI-generated images), the right orbitofrontal cortex and anterior cingulate cortex stand out, supported by the activation of the cuneus and precuneus; this pattern favours attention capture, visual value encoding and the formation of associated emotional memories. In the multisensory-associative circuit (more evident with real images), the involvement of the insula and right superior temporal lobe, along with left occipital and parietal areas, suggests an experience more rooted in bodily sensations and linked to the consumer's perceptual history. Both circuits can increase the likelihood of an impulsive response, albeit through partially different routes: the former through immediate visual appeal and sensory enhancement, and the latter through predictive congruence and interoceptive resonance.

From an applied perspective, these findings advise caution and promote transparency. Stimulation of orbitofrontal regions and the limbic system through AI-generated images can trigger purchasing impulses without the individual being fully aware of the source of that influence (Matukin et al., 2016; Pillpe et al., 2025). In contexts of repeated exposure in urban spaces, this effect can contribute to the consolidation of unhealthy habits. For responsible research and practice, it is recommended to: incorporate measures of hunger status and eating habits (Momot et al., 2025; Sawada et al., 2019); clearly disclose the origin of images, given sensitivity to authenticity (Califano & Spence, 2024; Nozawa et al., 2022); and evaluating the effects on perceived portion size and desire for consumption (Spence et al., 2016, 2022).

Overall, even though both cases involve unhealthy food, the nature of the stimulus consistently modulates the functional architecture of the brain's response. AI-generated images seem to enhance the attention-reward pathway, with a more compact activation pattern lateralised towards the right hemisphere; real images, on the other hand, recruit a more extensive network that incorporates interoception and sensory memory, in line with the perceived authenticity and experiential history of the consumer. This contrast allows us to understand why, depending on the context and the individual's state , the same product category can activate different persuasive routes and generate different behavioural effects.

7. Limitations

These findings should be interpreted as a snapshot of the current fast-food landscape, at a time when technological innovation and the constant evolution of consumer preferences are rapidly transforming the ways in which these products are communicated, perceived and chosen. Examples such as the incorporation of dishes originally perceived as healthy or exotic (e.g., sushi or poke) into fast-food circuits illustrate how the commercial and cultural context reconfigures the perception of what is meant by "fast food." However, a basic and instinctive behavioural substrate persists in our relationship with food that transcends these fads and adaptations.

It is important to note that the results of this study are applicable only to the cultural context of the participants, so caution should be exercised when generalising them to other sociocultural environments. Differences in norms, values, and eating habits can substantially modulate both perception and neurocognitive response to the stimuli evaluated.

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