The influence of AI-generated versus real food images on perceived value and negative WOM

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Declaration on the Use of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work, the authors used ChatGPT to improve English language quality and address writing-related issues such as grammar, clarity, and style. After using this tool, the authors carefully reviewed and edited the content as needed and take full responsibility for the content of this publication. In addition, the final version of the manuscript has been revised by a professional proofreading service.

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Abstract

Purpose: As the use of generative AI in food marketing continues to grow, understanding how consumers evaluate AI-generated imagery has become increasingly important. In this article a comparison is made of how AI-generated images and real images influence consumers' perceived value and negative word-of-mouth (WOM) intentions through the mediating effects of pleasure and perceived risk.

Design/methodology/approach: This study draws on decision-making theory, the cost–benefit paradigm and affect heuristic theory. Data were collected through an online survey distributed to 241 Spanish consumers, who were randomly exposed to either AI-generated (with an AI disclosure label) or real food images. Data were analysed using partial least squares structural equation modelling (PLS-SEM).

Findings: AI-generated food images, when compared to real food images, significantly reduce consumers' perceptions of value and increase their negative WOM. Pleasure and perceived risk mediate these effects, and consumers with more experience of AI are less prone to the adverse influence of AI-generated (vs. real) images on pleasure.

Originality/value: This research integrates emotional and cognitive processes and advances decision-making and affect heuristic frameworks by revealing how pleasure and perceived risk jointly shape consumer responses to AI-generated (vs. real) food imagery. Specifically, we confirm that emotion-based heuristics continue to play a decisive role in consumer decision-making, even in technologically mediated environments.

Practical implications: AI-generated imagery may diminish pleasure and heighten perceived risk, leading to less favourable consumer responses. Therefore, food marketers should ensure that AI-generated images retain a realistic and appetising appearance to prevent negative effects on perceived value and brand evaluations.

Keywords: AI-generated images, Food marketing, Perceived risk, Pleasure, Negative word-of-mouth, Perceived value

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1. Introduction

Artificial intelligence (AI), much like the internet some decades ago, has rapidly become a mainstream force transforming industries and redefining how companies operate (Dabija and Frau, 2024). Firms in many sectors are dramatically increasing their investments in AI to enhance productivity and competitiveness (Boston Consulting Group, 2025). AI is progressively being integrated throughout the entire value chain, revolutionising production, delivery and consumption processes (Chakraborty, 2025; Frau and Keszey, 2024). According to a global survey of nearly 1,500 industrial managers conducted by McKinsey and Company (2025), marketing is the leading business function where companies have begun to apply AI technologies.

AI has evolved from an emerging trend to a transformative force that is reshaping marketing and branding practices. It has become the new normal in marketing, driving content personalisation, storytelling and customer engagement (Dabija and Frau, 2024). From predictive analytics and recommendation systems, to generative content creation, AI enhances the efficiency and effectiveness of marketing operations (Chintalapati and Pandey, 2022). The recent evolution of generative AI (GenAI) powered by Large Language Models (LLMs) has accelerated this transformation: firms now deploy AI agents to provide personalised offerings to customers in a highly cost-effective manner (Hermann and Puntoni, 2025). The success of tools such as ChatGPT, Sora and MidJourney illustrates how generative models have rapidly expanded across industries (Belk et al., 2023): image creation has emerged as one of the first marketing applications of AI. These developments rely on algorithmic generation to boost brand expression, offering marketers unprecedented scalability, creativity and affordability. In the United States, 39% of marketers employ AI to create images for social media, while 36% use them on their own websites (Statista, 2023a). GenAI is revolutionising how brands communicate visually, producing hyper-realistic, context-aware images that can equal or even surpass human-generated content in aesthetics, quality and engagement (Hartmann et al., 2025).

However, the integration of GenAI into branding raises critical theoretical and managerial questions about how synthetic imagery affects visual brand identity (Phillips et al., 2014) and consumers' perceptions. Visual brand identity is the coherent visual style that signals a brand's essence, beyond basic logos or colours. When AI systems generate branded imagery, they may unintentionally distort or reinterpret these visual cues, creating tension between expected and perceived authenticity (Philips et al., 2014). Understandably, practitioners are not agreed about whether consumers accept that brands should use AI-generated images to communicate their offerings: a recent North American survey found that 60% of consumers support marketers' use of AI to create content, while 24% disapprove (Statista, 2024). Conversely, a global study revealed that 47% of consumers feel uncomfortable with advertising that uses AI-generated product images, compared to 39% who feel comfortable and 14% who are unsure (YouGov, 2025). These mixed reactions suggest that AI-generated images can disrupt established brand schemas and reduce positive affect and attachment when they deviate from familiar, coherent visual patterns (Phillips et al., 2014), this deviation altering perceived authenticity and consumer responses towards the brand.

Recent studies call for marketing research to examine how AI-generated images interact with visual brand identity and consumer (dis)trust. There is an open debate about the advantages and disadvantages of using AI-generated imagery. Hartmann et al. (2025) demonstrated that AI-generated imagery can outperform human-made visuals in terms of creativity and effectiveness when the synthetic nature of the AI images is undisclosed. In turn, Belanche et al. (2025b) found that brands should not use AI-generated images when promoting high involvement products, because consumers perceive AI imagery as impersonal and lacking emotion and veracity, which creates distrust towards brands. Previous research comparing the features of real versus AI-generated images concluded that, when compared to authentic, real images, AI images tended to omit imperfections (Miller et al., 2023), lacked a human touch (Belanche et al., 2025b) and deviated from the true appearance (e.g., disproportionate portion size, Califano and Spence, 2023). This suggests that AI-generated images raise in consumers risk concerns related to lack of authenticity and the performance of the brands deploying the images, which represents a novel and underexplored challenge for visual branding imagery. In this line, Grewal et al. (2025) stressed the need for marketing scholarship to explore the strategic alignment between AI capabilities and brand positioning, warning that misalignment may weaken brands' symbolic coherence and human touch. Thus, as firms increasingly adopt GenAI to produce visual content, a research gap emerges: there is a need to understand the process by which brands which use AI-generated images, rather than actual images, can preserve consumer perceived value and avoid negative reactions, based on their capacity to create for consumers a pleasant experience and minimise their perceptions of risk. In addition, this process may vary based on consumers' characteristics, which remain largely unexplored to date (e.g., age, Zelený et al. 2023) and, thus, merit further attention.

In the food sector analysed in the current research, comparing AI-generated and real images is especially important because, unlike in other product categories, consumers primarily evaluate food based on the pleasure and sensory appeal conveyed by the imagery (Mela, 2006). Food brands rely heavily on visual cues to communicate sensory pleasure, authenticity and trust—attributes that are fundamental to their positioning and consumer relationships. The use of AI-generated food images, therefore, represents more than a technical innovation; it challenges the emotional and symbolic foundations through which brands communicate the taste, naturalness and quality needed to persuade consumers. For instance, Chan (2024) found that realistic AI-generated images of food are perceived as being tastier than, and increase purchase intentions for, hand-drawn style AI-generated imagery. However, previous research has not examined consumers' perceptions of risk and negative reactions towards brands employing AI-generated images, the most common alternative practice to using real images. As noted by recent research (Dabija and Frau; 2024; Califano and Spence, 2024; Frau and Keszey, 2024), the agri-food sector is undergoing a digital transformation that, to sustain brand equity and consumer trust, demands a balance be struck between technological efficiency and emotional authenticity. Studying AI-generated imagery used in food marketing extends the knowledge of consumer decision-making in relation to visual branding, and provides managerial insights into the process by which these images influence marketing effectiveness and consumer behaviours.

To advance understanding of consumers' visual evaluations of food imagery, the present research applies decision theory (Savage, 1954), the cost–benefit paradigm (Einhorn and Hogarth, 1981) and affect heuristic theory (Slovic et al., 2007) to this novel phenomenon. Building on prior research (Haase et al., 2018; Belanche et al., 2025b) we posit that, in food marketing, the core benefit derived by the consumer is the pleasure evoked in him/her by the image, whereas the main perceived cost relates to performance risk perceptions, which arise when the (s)he questions the reliability and authenticity of the representation. Following affect heuristic rationale, greater expected pleasure is expected to reduce perceived risk (Alhakami and Slovic, 1994; Slovic et al., 2007). Furthermore, consumers' value perceptions are conceptualised as the trade-off between benefits and costs, while negative word-of-mouth

(WOM) represents a potential behavioural response that can harm the reputation of brands employing AI-generated imagery. Accordingly, we propose the following research questions:

RQ1: *Can AI-generated food images, when identified as such by the advertiser/company, evoke pleasure expectations comparable to those elicited by real food images?*

RQ2: *Do AI-generated food images, when identified as AI, lead to greater risk perceptions among consumers than do real food images?*

RQ3: *To what extent does the use of AI-generated images by companies reduce consumers' perceived value, and increase negative WOM?*

This research makes several key contributions to the emerging literature on AI-generated visual content in branding and food marketing. First, contributing to the ongoing debate about the value for companies of using AI-generated imagery, we empirically test how images identified as AI-generated influence consumer responses relative to real images, and propose a novel research framework based on previous theoretical foundations (e.g. Slovic et al., 2007) to help explain this process. In particular, extending previous theoretical insights gained in visually driven consumption contexts (e.g., Mela, 2006), we propose that the expected pleasure elicited by real images operates as an affective heuristic that reduces perceived risk, whereas the opposite effect occurs with AI-generated images. Second, our research enhances understanding of the psychological and behavioural implications of using AI-generated imagery, a topic largely neglected in prior research, by examining how pleasure and risk perceptions shape the consumer's value assessments, a crucial variable in marketing and branding, and his/her negative WOM intentions, that is, his/her negative reaction: negative WOM caused by AI-generated imagery is almost unexplored in this novel research context (Brüns and Meißner, 2024). Finally, recognising that perceptions of AI authenticity vary across consumer segments (Zelený et al., 2023), this study examines prior experience with AI, and age and gender as moderating factors, to offer a more nuanced view of how individual differences shape responses to visual formats.

By applying established knowledge to the emerging phenomenon of branding through AI-generated imagery, with a focus on the agri-food sector, our study provides practical proposals for marketers and brand managers. In particular, we encourage practitioners to weigh the advantages against the drawbacks of using AI-generated images in terms of consumers' perceptions and responses. In addition, we identify actions to mitigate the negative consequences of this increasingly common practice, such as loss of value and reputational harm.

2. Literature review and theoretical background

2.1. AI-based marketing communications in the agri-food sector

AI has rapidly become a mainstream force, transforming industries, including the agri-food (Dabija and Frau, 2024). Research into AI applied to the agri-food sector has primarily focused on firms' implementation of the technology to improve efficiency in logistics, control of food quality and safety, and product innovation (Trabelsi et al., 2023; Frau and Keszey, 2024). The food technology market, valued at $260 billion in 2022, is projected to grow to $360 billion by 2028, highlighting the sector's momentum (Statista, 2023b). Yet, although academic interest in AI is increasing, much of the existing literature on AI implementation in the agri-food sector remains conceptual (Trabelsi et al., 2023), leaving many practical aspects of this disruptive technology insufficiently explored. Comparing AI-generated images with real images is particularly important in this sector as consumers' food preferences are often based on how advertisement images appeal to the senses and hedonic experiences (Mela, 2006). However, the literature remains fragmented and underdeveloped, particularly regarding consumer responses to artificial images. Table 1 summarises previous research on the use of AI-generated images in the food industry.

INSERT TABLE 1 HERE

While prior studies have explored whether consumers can usually distinguish between AI-generated and real images of food (Califano and Spence, 2024; Zelený et al., 2023), the broader implications of this distinction on psychological processes, and the relationship between consumers and brands that employ AI-generated images, remain insufficiently understood. Previous literature suggests that, when the consumer is aware an image is AI-generated, the product's perceived healthiness and/or desirability is reduced (Stright et al., 2025), and that some consumers experience discomfort when exposed to near-realistic AI food images (Diel et al., 2025); nevertheless, most of these studies are generally conceptual and/or exploratory, and often focus on AI recognition, without going deeper into the psychological and behavioural consequences associated with the process.

As AI-generated images become increasingly prevalent in commercial food communications (Diel et al., 2025), both scholars and practitioners need to understand how images identified by the advertiser/producer as AI-generated affect key marketing outcomes, when compared to real food images, by focusing on consumers' psychological processes. Previous studies examining the impact of AI-generated food images on consumer responses relied on partial approaches grounded in transparency and ethics (Califano and Spence, 2024), the potential existence of the uncanny valley effect in food contexts (Diel et al., 2025) and/or the distinction between hedonic and utilitarian value (Stright et al., 2025). Recent research has also explored how AI-generated imagery influences the expected value of brand offerings (Chan, 2024), for example, realistic AI-generated images lead to more favourable taste perceptions, and higher purchase intentions, than do hand-drawn styles, although both stimuli are AI-generated. To advance this line of research, we propose an integrative framework grounded in established theoretical foundations to explain how food-related visual imagery shapes consumers' perceived value and negative WOM intentions, through the mediating roles of expected pleasure and perceived risk.

2.2. Decision theory and the cost-benefit paradigm in food marketing

Decision theory (Savage, 1954) and the cost–benefit paradigm (e.g., Einhorn and Hogarth, 1981) offer a robust foundation for understanding how individuals evaluate alternatives and make judgments under conditions of uncertainty. These perspectives propose that decision-makers seek to maximise expected utility by weighing perceived benefits against potential costs, or risks, forming subjective beliefs about the evaluated content. This paradigm has proven useful in numerous marketing and technology contexts. For instance, Belanche et al. (2025a) found that consumers evaluate FinTech AI tools based on their expected benefits and associated performance risks, while Morosan and Dursun-Cengizci (2024) showed that, in hospitality services, the decision to use AI systems is positively influenced by perceived convenience and efficiency, but negatively affected by risks such as potential failures and/or loss of control. However, consumer decisions in food marketing differ from those in service technology contexts. In food communications, the benefits consumers seek are mainly hedonic—related to sensory pleasure and emotional satisfaction—whereas perceived costs are psychological and perceptual, often involving risk judgments regarding the reliability and quality of the food service behind the image (Mela, 2006; Haase et al., 2018). Accordingly, cost–benefit logic must be adapted to capture the affective and sensory nature of decision-making in this domain.

2.3. *Affect heuristic theory in food marketing*

Complementing this cost-benefit perspective, affect heuristic theory (Slovic et al., 2007) provides a psychological account of how emotional and intuitive processes guide consumers' judgments of benefits and risks. This theory posits that people often rely on affective impressions (i.e., feelings of liking or disliking) rather than analytical reasoning when evaluating objects, products or brands in uncertainty conditions. As Epstein (1994) explained, the experiential system activates affect-laden memories that prompt approach or avoidance behaviours: pleasant feelings prompt people to take actions expected to reproduce these feelings, whereas unpleasant feelings prompt avoidance behaviours. Damasio (1994), similarly, argued that experiences become "marked" with negative or positive affective tags. Negative tags may sound alarms in the individual while positive tags can trigger constructive thoughts/behaviours and provide incentive. This forms an "affect pool" that individuals unconsciously consult in their decision-making (Slovic et al., 2007). These affective cues act as mental shortcuts that substitute for effortful reasoning when evaluating potential outcomes. In the words of early affect theorist Zajonc (1980), people buy the cars they "like" and choose the houses they find "attractive," justifying their decisions afterwards with various reasons.

Within this framework, judgments of risk and benefit are not independent cognitive assessments, but two sides of the same affective coin. Alhakami and Slovic (1994) showed that when people associate an activity or product with positive affect, they judge it as high in benefit and low in risk, and vice versa. For example, the tobacco industry's long-term use of emotionally appealing imagery (e.g., freedom, nature, a rugged cowboy) successfully increased consumers' perceptions of the pleasure of smoking and, consequently, depressed their perceptions of the health risks (Slovic et al., 2007). Similarly, when individuals view city images, they tend to prefer those linked to positive affective attributes such as "good beaches" over those associated with negative attributes such as "crowded," even when all other objective information/stimuli are the same (Slovic et al., 1991). These findings illustrate that factual reasoning need not be the only basis for risk evaluation and decision-making: pleasant expectations can also have a strong influence.

3. Hypotheses development

The hypotheses developed in this section conform to the framework depicted in Figure 1. Previous literature has established that food images strongly stimulate hedonic motivations and the expectation of enjoying positive emotions (Pérez-Villarreal et al., 2019). In food advertising, the pleasure derived by the viewer from visual stimuli is closely tied to emotional resonance and the capacity of images to evoke sensory feelings and appetitive desires (Mela, 2006). When a person perceives that a goal is attainable—such as tasting the food depicted in an image—positive expectations about achieving that goal are activated (Bagozzi et al., 2016). Indeed, pleasurable food images can even trigger activity in the gustatory and olfactory regions of the brain, reinforcing the expectation of sensory enjoyment (Pelchat et al., 2004). Through these mechanisms, real food images tend to create vivid and embodied mental simulations that heighten consumers' expected pleasure.

INSERT FIGURE 1 HERE

However, when the visual stimulus is artificially generated, the emotional response may weaken. AI-generated images, although technically proficient, often convey a sense of artificiality and emotional distance (Hausken, 2024). They lack the human intentionality and contextual authenticity that characterise real photographs, which capture spontaneous cues of emotion and sensory richness (Belanche et al., 2024; Hausken, 2024). Moreover, AI-produced visuals frequently include atypical or subtly distorted elements that interfere with the natural processing of visual information (Landwehr et al., 2013), thereby reducing emotional fluency and hedonic response. As a result, the mental simulation they prompt may be less vivid, producing lower expectations of pleasure than does genuine food imagery.

Affect heuristic theory (Slovic et al., 2007) offers a consistent psychological explanation for this difference. This theoretical perspective posits that individuals often rely on affective impressions (i.e. pleasant or unpleasant feelings) rather than deliberate reasoning when judging objects or stimuli in uncertainty conditions. Applied to food marketing, this means that real food images evoke familiar, sensory-rich experiences in which viewers can almost "taste" or "smell" the product, thereby triggering positive affective responses and higher expected pleasure. In contrast, AI-generated images are affectively less precise and lack emotional grounding, which reduces their evaluability and the consumer's confidence about whether (s)he is capable of making a good decision. According to the evaluability principle in affective heuristic theory (Slovic et al., 2007), the clarity and precision of affective meaning influence the direction and strength of the viewer's evaluations. Thus, when affective meaning is vague or ambiguous, as with AI-generated stimuli, individuals experience uncertainty and weaker affective engagement, leading to diminished expected pleasure.

H1: AI-generated images generate less expected pleasure in the consumer than do real images.

Perceived risk has been defined as the degree of uncertainty and the possible negative outcomes that consumers associate with a purchase decision (e.g., Mitchell and Boustani, 1994). Understanding and mitigating consumers' perceived risk is crucial, as it directly affects their decision-making processes and subsequent purchasing behaviours (Mitchell and Boustani, 1994).

When confronted with an image, consumers instinctively assess the reliability and validity of its origin (Chan, 2025). In the realm of authentic images, the source is often associated with traditional photography, which has conventionally been considered an accurate representation of reality (Hausken, 2024). A professional photographer brings a human touch to what the company wants to show, along with control over the final image (Whittaker et al., 2020). In contrast, AI-generated images represent a novel source that can be perceived by the viewer as ambiguous and unverified, which generates in him/her greater uncertainty and intrinsic fears related to manipulation and deception (Grigsby et al., 2025). When presented with an AI-generated image, consumers might doubt the competence and transparency of the sponsoring company, and even question whether it is trying to deceive them (Belanche et al., 2025b). This ambiguity is closely linked to consumers' concerns regarding the lack of accuracy and authenticity and/or the inherent bias in AI (Grigsby et al., 2025). This diminished perception of authenticity in AI-generated imagery may sow doubt among consumers about the accuracy of the information conveyed, thereby increasing the perceived risk associated with taking decisions based on the images (Bui et al., 2024).

H2: AI-generated images generate more perceived risk in the consumer than do real images.

When consumers experience significant pleasure related to a particular product or experience, they tend to focus on the positive and rewarding elements of that experience (Varshneya and Das, 2017). This favourable orientation may hide the visibility of potential adverse outcomes or uncertainties associated with decision-making, thereby reducing risk perceptions.

Consumers experiencing positive emotions can influence cognitive evaluations and promote a less threatening interpretation of a situation (Babin et al., 1994). In fact, pleasure experienced can act as a psychological compensatory mechanism for perceived risks (Baumann et al., 1981). This view aligns with the fundamentals of affect heuristics, which propose a negative correlation exists between pleasant feelings and risk perceptions (Slovic et al., 2007), a finding previously documented in the literature (Alhakami and Slovic, 1994). The expectation or attainment of pleasure may lead consumers to disregard certain risks, as they consider emotional rewards to be intrinsically valuable. For instance, the positive emotions derived from the activity by shoppers can outweigh the associated risks (Thompson et al., 1990). Ultimately, when consumers derive greater pleasure, this fosters in them more favourable attitudes, and reinforces their confidence in the product, thereby mitigating perceptions of uncertainty and, consequently, perceived risk. Thus, when a viewer has positive perceptions of a food image this may enhance his/her belief that the benefits of consuming it outweigh the associated risks (Alhakami and Slovic, 1994; Said et al., 2023).

H3: Higher levels of expected pleasure are associated with lower levels of perceived risk.

Many empirical studies have illustrated that hedonic elements are a critical dimension of perceived value (e.g., Sweeney et al., 2019; Gursoy et al., 2019). A more pleasurable experience is deemed to possess augmented overall value, as it meets the consumer's emotional and sensory expectations.

Perceived value is found not only in a product itself, but also in how consumers engage with it and the surrounding context (Varshneya and Das, 2017). For instance, in the digital marketplace, value creation for the consumer focuses on experiences that enhance pleasure, marking a transition from traditional commodity-centric frameworks to frameworks that emphasise consumer satisfaction and emotional connectivity (Karpunina et al., 2020). In addition, pleasure has been shown to function as a mediating element in consumers' engagement with service robots, increasing their propensity to use these technologies because they provide enjoyable and gratifying experiences (Alam et al., 2024). As consumers seek pleasure in food consumption (Pérez-Villarreal et al., 2019), we apply this theoretical rationale to the food marketing sector.

H4a: Higher levels of expected pleasure are associated with higher levels of perceived value.

Negative WOM is the informal communication of unfavourable views by consumers about a product (Yim, 2024). Negative WOM often arises from consumer dissatisfaction, can manifest itself in various forms, and can have a significant impact on consumer behaviour and perceptions. For example, in the context of social media, negative WOM can spread rapidly, lead to serious reputational crises, where collective outrage is directed against a single entity, often resulting in the swift and widespread dissemination of negative sentiment (Wako et al, 2024), affecting purchase decisions and sales (Dong et al., 2024).

When consumers experience low pleasure, they are more likely to engage in negative WOM to express their dissatisfaction and share their negative experiences with others (Sukhu and Bilgihan, 2021). This is because hedonic values are closely linked to emotional responses, and negative emotions can lead consumers to voice their dissatisfaction (Wako et al., 2024).

H4b: Higher levels of expected pleasure are associated with lower levels of negative WOM.

The academic literature consistently indicates that an inverse correlation exists between perceived risk and perceived value (e.g., Sweeney et al., 1999). When consumers perceive risk to be high, this lowers their expectations of perceived quality and/or amplifies their perceptions of overall sacrifice (although not exclusively economic), resulting in a decline in their overall evaluations (Lapierre, 2000). For instance, in technology purchases, if consumers foresee a significant performance risk due to the technology malfunctioning, their perceptions of the product's overall value decreases significantly (Yu et al., 2017). Moreover, Cronin et al. (2000) showed that the perception of increased costs (financial sacrifice, a manifestation of perceived risk) is inversely related to perceived value.

H5a: Higher levels of perceived risk are associated with lower levels of perceived value.

Previous research suggests that perceived risk has a positive relationship with negative WOM (e.g., Nam et al., 2020). When consumers assess that the high risk of making a consumption decision outweighs the advantages they might derive from making the decision they are more inclined to share their apprehensions and adverse experiences with others. For example, when consumers realise that using a product involves a significant cost, they may experience a sense of injustice, which can consequently prompt them to spread negative WOM as a means of expressing their negative feelings (Dalzotto et al., 2016).

(Talwar et al., 2021). To alleviate this psychological unease, they might opt to share their negative experiences with others to validate their feelings and help others avoid similar mistakes. This effect could be particularly important in the AI domain, as it has been observed that consumers engage more in negative WOM when they experience a heightened sense of threat (Zhang et al., 2022).

H5b: Higher levels of perceived risk are associated with higher levels of negative WOM.

For the sake of completeness, we also include consumers' previous experience with AI, and age and gender as moderating variables that may affect the influence of image type (AI-generated vs. real) on expected pleasure and perceived risk. These individual factors may be critical to understanding consumers' reactions towards disruptive technologies (e.g., Belanche et al., 2015), that is, moderating effects based on these characteristics might explain how the influence of image type might vary across consumers.

4. Methodology

4.1. Data collection and estimation procedure

Data collection was carried out through an online questionnaire in Google Forms addressed to Spanish consumers in June 2024. Spain was chosen as, first, it has a mature and competitive restaurant market that plays a significant role in the national economy and, second, it is undergoing a decisive phase of digital transformation (Martín-Martín et al., 2022), with AI adoption above the EU average (European Commission, 2024). This makes it an appropriate context for exploring consumers' reactions to AI-generated food images used by restaurants. The survey participants were initially provided with information on the scientific purpose of the study and data protection, were told the study was anonymous, and gave their explicit informed consent to taking part. Then, the participants were presented with a hypothetical situation, an image showing food in a restaurant setting, either an image generated by AI, or a real image. To attract a variety of participant responses we used twelve images (six generated by AI, and six real images). Six images depicting authentic food (e.g., hamburgers, ice creams) in context (e.g., restaurants) were obtained from the internet. Subsequently, six comparable AI-generated images were created by entering iterative descriptions of the original images as prompts in DALL-E, with the aim of reproducing images with similar visual characteristics. The participants, to ensure the internal validity of the experiment, were then randomly assigned to view one of the twelve images (e.g., Shadish et al., 2002). When presented to the participants, the AI-generated images were clearly labelled with the tag "AI-generated image" (see Appendix I).

Thereafter, the participants answered the questionnaire (see Appendix II). To guarantee their content validity, scales were adapted from previous literature. The questionnaire included a question to confirm that the participants had correctly identified whether the image had been generated by AI or was a real image (for the analyses, image type was included as a dummy variable, coded as follows: 1=image generated by AI; 0=real image). Finally, although restaurant brand names were not provided, we checked the perceived realism of the hypothetical situation (i.e., evaluating restaurant advertisements based on food images presented to participants) following Bagozzi et al., (2016). This process confirmed that the situation was perceived as realistic (M=4.964, which is significantly higher than 4, the central point of the scale [t= 10.381; p<0.01]). Sociodemographic characteristics (age, gender, education) were also measured.

Following these checks, we were left with a total sample of 241 participants. The sample had balanced sociodemographic characteristics in terms of gender (male 49.79%, female 46.89%, other 2.49%, and prefer not to disclose 0.83%), age (less than 25 years, 22.82%: 25-34 years, 40.66%: 35-44 years, 17.84%: 45 years or more, 18.67%) and education (secondary/high school studies 26.97%, university studies 73.03%).

4.2. Measurement validation

As depicted in Table 2, all composite reliability (CR) values are higher than 0.7 (Straub, 1989), and the Cronbach's alpha values are well above the cut-off value of 0.7 (Nunnally, 1978). In addition, factor loadings are greater than 0.7 (Henseler et al., 2015). One item of the expected pleasure scale was eliminated as its factor loading was lower than this cut-off value. Next, we tested convergent validity by confirming that the average variance extracted (AVE) values were greater than 0.5 (Fornell and Larcker, 1981).

INSERT TABLE 2 HERE

Discriminant validity (see Table 2) was confirmed as, for each construct, the square root of the AVE was greater than the inter-construct correlation (Fornell and Larcker, 1981). We also observed that the heterotrait-monotrait (HTMT) ratios were below the cut-off value of 0.85 in all cases (Henseler et al., 2015).

Finally, we statistically tested for the presence of common method bias. In addition to procedural measures taken during the design of the research questionnaire (e.g., we guaranteed the participants anonymity, explained to them that there were no correct or incorrect answers, and avoided ambiguities in the items, complicated syntax and vague concepts [Podsakoff *et al.*, 2003]), we conducted a full collinearity test (Kock and Lynn, 2012). Following Kock (2015), the conclusion can be drawn that the whole model is free of common method bias, given that all factor-level variation inflation factors are lower than 3.3.

Results

The proposed model was tested using PLS (SmartPLS4; Ringle et al., 2024), and a bootstrapping procedure (10,000 bootstrap sub-samples) was used to assess the significance of the coefficients. We confirmed the overall fit of the structural model with the standardised root mean square residual (SRMR), obtaining a value of 0.046, below the cut-off value of 0.08 (Hu and Bentler, 1998). Figure 2 shows the results of our analyses.

INSERT FIGURE 2 HERE

First, we observed that AI-generated images prompted less expected pleasure (β= -0.595; p< 0.01) and more risk (β= 0.778; p< 0.01) than did real images, supporting H1 and H2, respectively. Second, it was seen that expected pleasure reduced risk (β= -0.460; p< 0.01) and negative WOM (β= -0.230; p< 0.01), but increased perceived value (β= 0.435; p< 0.01), which supports H3, H4b and H4a respectively. Third, perceived risk reduced perceived value (β= -0.467; p< 0.01) and increased negative WOM (β= 0.610; p< 0.01), supporting H5a and H5b.

Turning to the moderating effects, which were calculated employing a two-stage approach (e.g., Becker et al., 2018), we obtained mixed results. Specifically, experience of AI significantly reduced the effect of image type on pleasure (β= 0.298; p< 0.05). This moderating effect is represented in Figure 3; as experience with the use of AI increases, the difference in expected pleasure between image type is reduced. However, experience of AI did not affect the relationship between image type and risk. Finally, the moderating effects of age and gender on the influence of image type on both pleasure and risk were not significant.

INSERT FIGURE 3 HERE

These relationships partially explained the dependent variables of our model: expected pleasure (R^2 = 0.160), perceived risk (R^2 = 0.445), perceived value (R^2 = 0.640) and negative WOM (R^2 = 0.585). Table 3 provides a summary of the results, indicating whether the hypotheses were supported.

INSERT TABLE 3 HERE

4.3. Post-hoc analysis: Mediating effects

Our research model proposes that pleasure and risk mediate the relationships between image type and the dependent variables, perceived value and negative WOM. Accordingly, we further analysed these potentially mediated relationships. Specifically, we calculated the bias-corrected and accelerated confidence intervals of the effects (Chin, 2010; Zhao *et al.*, 2010). The indirect effects in each sample are used to build confidence intervals, with these effects being significant if the intervals exclude the value 0. Table 4 shows the results of our analyses. The results, first, confirm that image type exerts an indirect effect on perceived value via pleasure (confidence interval [CI]: -0.418; -0.109), risk (CI: -0.529; -0.225) and pleasure and risk (CI: -0.211; -0.054). Similarly, image type exerted an indirect effect on negative WOM via pleasure (CI: 0.051; 0.240), risk (CI: 0.299; 0.678) and pleasure and risk (CI: 0.070; 0.271). These indirect specific effects showed that there was a significant indirect total effect of image type on both perceived value (CI: -0.997; -0.495) and negative WOM (CI: 0.539; 1.014). As there are no direct effects, indirect total effects are equal to total effects, which suggests that lower perceived value and higher negative WOM are expected for AI-generated than for real images.

INSERT TABLE 4 HERE

To check whether the mediation is partial or total, we also estimated an extended version of our research model to include the direct effects of image type on perceived value and negative WOM (see Table 5). The results revealed that the direct effect of image type on perceived value is significant (β= -0.231; CI: -0.404; -0.041), but its direct effect on negative WOM is non-significant (β= 0.145; CI: -0.047; 0.345). Therefore, while the influence of image type on negative WOM was seen to be fully mediated by pleasure and risk, the relationship between image type and perceived value is partially mediated by both pleasure and risk.

INSERT TABLE 5 HERE

5. Discussion

The present study explains the process through which consumers assess AI-generated images in the food sector, contributing to the ongoing debate about their use in visual brand imagery (Grewal et al., 2025). The findings showed that AI-generated food images, when their origin is explicitly disclosed, decrease consumers' expected pleasure, and increase their perceived risk, in comparison to real food images. This outcome aligns with earlier studies that indicated that consumer awareness of artificial content tends to weaken their emotional engagement and heighten their reliability-based scepticism (Stright et al., 2025; Grigsby et al., 2025). These results reaffirm that, in evaluations of food, pleasure functions as a key source of perceived benefit (Mela, 2006), in line with previous research that indicated that food image realism positively affects taste perceptions and purchase intentions (Chan, 2024).

The strong negative effect of perceived pleasure on risk accords with affect heuristic theory (Slovic et al., 2007), which suggests that positive emotional reactions mitigate threat perceptions. When consumers experience enjoyment from a visual stimulus, they are more likely to overlook uncertainty concerns, as they tend to attribute distrust and even deception to AI-generated images (Belanche et al., 2025b). The hedonic tone of the real image, and its authenticity, thus operate as an emotional shortcut, mitigating consumers' risk perceptions and encouraging a more favourable evaluation.

Our mediation tests revealed that the use of AI-generated images had a negative effect on perceived value, this influence being partially mediated by pleasure and risk perceptions: thus, AI imagery has an impact on brand evaluations. In particular, as hypothesised, pleasure increases, and risk decreases, value perceptions of consumers. In contrast, our analyses revealed that AI-generated images did not have a direct impact on negative WOM, rather that this negative influence is fully mediated by pleasure and risk perceptions. This interesting effect underscores the pivotal role of pleasure and risk in determining consumers' potential negative reactions towards brands using AI-generated imagery. This finding also expands the previous, scarce research into how using AI-generated content damages brand reputation (which, in any case, had been limited to analysing followers' reactions on social media, Brüns and Meißner, 2024): we offer a different perspective. Taken together, these effects portray a coherent decision-making process in which hedonic and risk appraisals interact to shape consumers' responses to AI-based visual communications, complementing previous studies that did not consider the causality between variables (e.g., perceived taste, purchase intentions, Chan 2024).

The moderation analysis adds an additional layer of insight. The consumer's previous experience with AI reduced the negative influence of AI-generated images on pleasure, suggesting that individuals familiar with this technology evaluate AI-generated images more favourably. This supports the notion that familiarity diminishes affective resistance, and facilitates the normalisation of artificial content (Zelený et al., 2023). Interestingly, neither age nor gender were significant moderating variables. This non-significant result suggests that the psychological mechanisms embedded in the model operate similarly across demographic segments. In other words, the pleasure and risk perceptions elicited in consumers by AI-generated food images appear to be general rather than demographically contingent. This finding aligns with prior research indicating that, when stimuli involve immediate sensory or emotional cues, demographic factors tend to play a limited role in shaping evaluative processes (e.g., Mela, 2006; Bagozzi et al., 2016). It also suggests that the perception of pleasure and risk in this context depends more on factors beyond sociodemographic attributes. Overall, these findings reinforce the proposed framework and highlight the dual dynamic by which hedonic and risk evaluations jointly determine consumers' reactions to AI-generated food images.

5.1. Theoretical Implications

This research contributes to theory by integrating emotional and cognitive processes into the understanding of how consumers evaluate AI-generated food imagery. It extends decision theory (Savage, 1954) and the cost–benefit paradigm (Einhorn and Hogarth, 1981) by identifying pleasure and perceived risk as central mediators in the assessment of marketing stimuli. The evidence supports the argument that consumers rely on affective cues to simplify complex evaluations, consistent with the affect heuristic framework (Slovic et al., 2007). When a food image elicits pleasure, consumers perceive lower risk, which leads them to develop enhanced value perceptions and lower negative WOM intentions, demonstrating how affective experience informs decision-making under conditions of uncertainty.

In this regard, the study explains how AI-generated visual content alters consumers' evaluative processes, in comparison to authentic, real images. In particular, our findings revealed that in domains where sensory pleasure is fundamental, such as food-related visual imagery, the use of AI tends to weaken the consumer-brand emotional connection, thereby heightening consumers' risk perceptions and diminishing their value attribution. These results provide empirical evidence that, despite the advantages of greater efficiency, technological factors may harm consumers' affective responses and, consequently, influence their value perceptions in marketing communications. Thus, our research reveals that emotion-based heuristics continue to play a decisive role in consumer decision-making, even in technologically mediated environments. Overall, the findings contribute to both theory building and theory testing, as outlined by Colquitt and Zapata-Phelan (2007): we build theory by integrating prior frameworks into a unified explanatory model to explain how consumers evaluate an AI-generated visual stimulus, and we test theoretical assumptions regarding affect-driven decision-making within this novel technological domain.

Our findings also contribute to the ongoing debate regarding the limitations of generative AI in persuasive communication. While recent research highlights the efficiency and visual precision of AI-generated imagery (Hartmann et al., 2025; Miller et al., 2023), this study demonstrates that this technological progress does not automatically translate into positive consumer outcomes when pleasure and perceived risk are central evaluative drivers. The proposed model provides a psychological explanation for the mixed evidence reported in the literature, and suggests that practitioners should be cautious when employing AI-generated images. Specifically, affective immersion (i.e., the heightened pleasure evoked by real food) appears to be constrained by consumers' awareness of artificial generation which, in turn, elevates risk perceptions, reduces value attributions and, more importantly, increases negative WOM. In this sense, the present study aligns with Corley and Gioia's (2011) view that a valuable theoretical contribution should be both original and useful: original in proposing a novel model to explain the psychological evaluative process of AI-generated imagery, and useful in offering practical insights for marketers into the opportunities and risks associated with adopting emerging technologies.

5.2. Managerial Implications

From a managerial standpoint, the findings emphasised that managers should think carefully before employing AI-generated visuals in food marketing. Although AI offers clear benefits in terms of cost and efficiency (Grewal et al., 2025), its use in hedonic categories may inadvertently diminish consumers' pleasure, and increase their risk perceptions, thereby undermining their evaluations. For instance, a restaurant chain that replaces authentic menu photographs with fully AI-generated photographs may reduce production costs, but could also prompt scepticism among customers who perceive the images as artificial, reducing their value perceptions. Thus, brand managers should confirm whether using AI-generated imagery is being negatively evaluated by consumers and, consequently, balance the operational advantages of automation against potential perceptual drawbacks.

Our findings suggest that, for brands that rely heavily on sensory appeal, imagery that evokes pleasure remains fundamental to sustaining value perceptions and preventing adverse reactions. Traditional photography (Whittaker et al., 2020), or AI-enhanced images that are realistic and carefully controlled (Hartmann et al., 2025), seem to be more effective when the consumer's purchase motivation is rooted in sensory experience. For example, a bakery might use real photographs of its products in social media profiles, but apply subtle AI enhancement to improve lighting and composition, preserving sensory realism while achieving professional quality. When organisations opt for AI imagery, they must ensure it maintains strong sensory appeal and avoids visual cues likely to evoke doubt or detachment. Preserving coherence between the visual stimulus and consumers' expected experience with the brand can help minimise perceived risk and safeguard perceived value.

The moderating influence of prior AI experience suggests that meaningful segmentation opportunities exist. Brands addressing consumers with higher technological familiarity, such as digitally engaged audiences, might employ a greater degree of AI-generated imagery without eroding hedonic responses. For example, a canteen in a technological campus might include AI-generated visuals which demonstrate its innovation and creativity, while ensuring that the dishes depicted remain recognisable and appetising. Conversely, for mainstream or premium markets, prioritising natural and emotionally resonant visuals remains the safer route.

Finally, the study indicates that excessive dependence on AI-generated imagery could entail reputational risks, especially when visuals appear disconnected from genuine sensory expectations. A well-known illustration of this risk occurred when several food platforms faced public criticism after sharing AI-generated images that users described as "unnatural" and/or "unappetising", leading to negative WOM and the subsequent removal of the visuals (Swearingen, 2024). A balanced strategy combining technological efficiency with human creative oversight can help maintain the emotional bond between consumers and the brand. Ultimately, AI should complement rather than replace the visual elements that stimulate pleasure and reduce perceived risk, ensuring that innovation strengthens rather than weakens marketing effectiveness in food-related contexts.

5.3. Limitations and Future Research

Our research is based on a controlled scenario where AI-generated images were identified as such, which increases internal validity. However, this scenario may not reflect real-world ambiguity, where consumers are not always aware of the origin of an image. Future studies should complement our research model by exploring and testing consumer responses when the image origin (AI or real) is unknown or misattributed. Further research should also examine whether the sensory and emotional gaps identified here exist across different media types (e.g., video, interactive 3D images).

Finally, our study focused exclusively on Spanish consumers, but cultural and contextual factors may shape how consumers perceive AI in food advertising. Expanding the study to cross-cultural contexts or different target audiences (e.g., based on the customer's tier status with the brand) could enrich our understanding of AI acceptance and its pros and cons in marketing communication. Future research could also benefit from using experimental designs incorporating physiological or behavioural metrics (e.g., eye tracking, facial recognition, or click-through rates) to gain deeper insights into consumers' subconscious negative responses to AI-generated images.

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APPENDIX 1 – Example of real (left) and AI-generated (right) images employed in the study

APPENDIX 2 - Measurement scales

Pleasure (adapted from Babin et al., 2024)
I think this service could be very enjoyable
I think this service could make me feel good
I think this service could provide me a pleasured experience
I think this service could make me feel excited
I think this service could make me feel like a sense of adventure
Perceived Risk (adapted from Lee, 2009).
I think the company providing the service might not perform well
I think there will be something wrong with the performance of the service
Using this service would lead to a financial loss for me due to a bad service
Perceived Value (adapted from Jiménez-Castillo and Sánchez-Fernández, 2019).
I think the service suggested in the image has an acceptable quality
In my opinion, the service offered is good
The service offered provides high value
Negative WOM (Adapted from Talwar et al., 2021)
I would warn my friends and relatives not to choose this service
I would say negative things about this service to other consumers
I would definitely tell others not to use this service
Experience with AI (Adapted from Helm and Hesse, 2025; and Belanche et al., 2016)
Frequency of using AI for generating texts
Frequency of using AI for generating images
Frequency of sharing content generated with AI
Realism (Adapted from Bagozzi et al., 2016)
The scenario presented is realistic
The scenario presented is believable
How likely would you be to encounter a situation like the one described in the scenario? (from 1 = very unlikely to 7 = very likely)

Notes: All scales used seven-point Likert-type response formats, from 1 (“completely disagree”) to 7 (“completely agree”), except for consumer experience with AI, which range from 1 “never” to 5 “several times a day”. In italics, item eliminated during the measures validation process.