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Customer reactions to generative AI vs. real images in high-involvement and hedonic services

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ABSTRACT

Given the emerging opportunities of generative AI for business and marketing, many companies are wondering whether they should use images created through generative AI for commercial purposes. Prior research on hospitality communication has not solved this issue, as AI-generated images are occasionally promoted as effective marketing tools across various service contexts, while other scholars caution against their use due to the significant concerns they may trigger among consumers. Following a mixed-methods approach to find boundary conditions, our research reveals that consumers prefer hospitality services advertised with real images, rather than those featuring AI-generated images. Nevertheless, this effect is moderated by two key factors. In particular, the research reveals that the negative influence of using generative AI images on intentions to use and recommend the service are strengthened for hedonic rather than utilitarian services, and for highly rather than lowly involved customers. A qualitative study further explores the reasons behind this rejection, highlighting that customers perceive companies using AI-generated images as impersonal, less professional, lacking credibility, and potentially misleading, as they impede customers' ability to envision the actual experience. Implications for management suggest that, while generative AI holds promise for enhancing communication, companies should use AI-generated images with caution. The discussion also proposes future research directions to explore the broader implications of AI use in marketing.

1. Introduction

Artificial intelligence (AI) has undergone remarkable development in recent years, transforming from an initially theoretical discipline to an increasingly pervasive technology with practical applications in a multitude of fields. AI is defined as *"the use of computational machinery to emulate capabilities inherent in humans"* (Huang and Rust, 2021). It is a multidisciplinary field that combines computer and cognitive science and focuses on creating systems that can learn from data, make decisions, and perform complex tasks (Sablone et al., 2024). Within AI, generative AI has emerged as a transformative force in management and marketing because it offers innovative tools and techniques to improve efficiency, adapt content, and improve customer engagement (Kshetri, 2024). For instance, in the hospitality industry, generative AI applications are being implemented to enhance user experience and service value (Casaló et al., 2025) and to tailor companies' offerings to individual customer needs and preferences. This approach does not only improves customer satisfaction but also drives business growth by creating more targeted marketing strategies (Florido-Benítez, 2024), and offering new ways to create memorable and personalized experiences (Sigala et al., 2024), such as personalized travel advice for tourists (Fouad et al., 2024).

One of the most widely adopted capabilities of generative AI today is its use as a tool to enhance human creativity in communication and advertising, enabling the generation of images, scripts, music, and visual effects (The Conversation, 2024). Indeed, this rapidly evolving technology is emerging as a novel approach to autonomously create new content, such as images, text, and video, by learning patterns from existing data (Hashmi & Bal, 2024). This technology reduces costs while also speeding up the design and marketing process by enabling the complete generation of ads (e.g., altering the skin tone, body, age, voice, or gender of the person in the ad; Campbell et al., 2022). However, the

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use of generative AI also poses several challenges, noting the importance of understanding its applications and their potential impacts (both positive and negative) on consumers, businesses, and society at large (Kshetri, 2024; Mustak et al., 2023). Although the content created using AI algorithms promises to radically change the landscape of communication and marketing in the coming decades, its use often compromises the credibility of the content and is sometimes considered inappropriate (Arango et al., 2023). Although AI-generated content offers faster and more cost-effective alternatives to hiring professionals for these tasks, recent literature highlights that its implementation poses ethical challenges and demands careful planning to ensure successful integration (Al-Khatib, 2024; Fouad et al., 2024). For instance, consumers exposed to AI-generated images may perceive risks related to misinformation and manipulation (Campbell et al., 2022). Therefore, understanding consumer perceptions of content created by generative AI is particularly relevant. On one hand, consumers may value the creativity and intelligence that AI can contribute to content creation, especially in areas such as advertising. On the other hand, persistent concerns remain regarding content authenticity, trustworthiness, and risk of misinformation (Christensen et al., 2024).

Despite its growing interest, the emergent but still scarce literature assessing customers' reactions toward brands using images created by generative AI for commercial purposes shows conflicting results. Some studies have found that AI enhances the creative process and image aesthetics, making AI-generated images more likable than real ones, which in turn generates a positive outlook among customers (Chaisatitkul et al., 2024). In contrast, other studies support that customers respond more unfavorably to artificial images than real or human-created ones because they perceive that AI lacks authenticity, which harms brands using such technological tools in advertising or social media (Brüns & Meißner, 2024; Lee & Kim, 2024). Complementarily, Arango et al. (2023) demonstrated that consumers accept AI-generated images only in certain circumstances, such as potential donors of charitable organizations responding favorably to the use of AI-generated images of children because they safeguard the privacy of the beneficiaries, which would not be the case if real images were used.

Recent research on marketing communication in hospitality services also shows inconsistent findings regarding consumers' responses to companies that employ AI-generated content. Whereas some studies suggest that AI-generated responses to online reviews are more credible and attentive than those written by hotel employees (Koc et al., 2023), other authors revealed that AI responses to TripAdvisor comments are perceived as useless or lacking authenticity (Amos & Zhang, 2024). Similar debates emerge regarding the use of AI-generated images, with some studies finding that AI-generated food images are more appealing than real ones (Califano & Spence, 2024), while other studies have found that tourists have concerns about the authenticity and trustworthiness of AI-generated destination videos (Seo et al., 2025). Researchers also show some potential boundary conditions, such as the satisfactory use of virtual influencers to promote utilitarian products rather than hedonic experiences in hotels (Belanche et al., 2024b), or the advantages of using real rather than AI-generated images in restaurants when consumers are focused on product taste rather than on its healthiness (Chan, 2024). However, a research gap remains regarding whether visually similar images elicit favorable or unfavorable consumer responses, depending on whether the image is perceived as real or AI-generated, as well as the boundary conditions under which hospitality managers could take advantage of AI benefits by employing AI-generated imagery.

Therefore, given the novelty and enormous potential of generative AI, our research investigates the ability of this technology to influence consumer perception and its impact on the effectiveness of communication campaigns, with special emphasis on the boundary conditions that make the use of these images more appropriate in certain circumstances. To advance in this field, we focus on the context of hospitality, where consumer decision-making is based on visual representations of restaurants, hotels, and destinations, since promotional images' features and aesthetics are a crucial determinant of expectations and purchase intentions (Erdem & Swait, 2004). To analyze consumers' responses toward real versus AI-generated images, our research is grounded on the Processing Fluency Theory, proposed by Reber et al. (2004), which suggests that the ease with which a stimulus is processed directly influences affective and cognitive evaluations. This theory has been applied in various contexts, including the success of marketing campaigns (Kim & Jang, 2018), the analysis of perceived innovativeness in new product launches (Min, 2022), and the examination of consumer popularity and preferences (Melvill-Smith et al., 2022). Based on the assumptions of this theory, our research proposes that the authenticity of real images favors consumers' cognitive fluency and clear evaluation, whereas AI-generated images that exhibit signs of falsity hinder this fluency and lead to more critical and complex judgements (Reber et al., 2004). Our aim is to better understand this process and identify the basic boundary conditions under which this effect may occur, thereby guiding professional practice. Building on previous research, we argue that fluent processing is more relevant for hedonic services (where emotional experience is valued; Dhar & Wertenbroch, 2000) than for utilitarian ones, and in high-involvement decisions (which require more elaborate processing of the presented information; Petty et al., 1983) than in low-involvement decisions. Therefore, we propose that the commercial effectiveness of using images created by generative AI varies depending on whether the service is hedonic or utilitarian, and whether the purchase is a high or low-involvement decision.

Based on the literature review on this novel phenomenon and the key aspects of consumer behavior that have not yet been applied to this context, this paper aims to answer the following research questions:

RQ1. . Do images created through generative AI (versus real images) affect consumers' behavioral intentions to use and recommend a hospitality service differently?

RQ2. . In which cases is it better to use generative AI or real images in hospitality: in utilitarian or hedonic services? In services with high or low consumer involvement?

RQ3. . What thoughts arise in customers when a hospitality company uses AI images (versus real images) to promote its services?

The contribution of the current research to the field is threefold. First, we analyze the impact of generative AI versus real images on customers' reactions toward the companies employing mixed methods, both quantitatively and qualitatively. In doing so, we clarify whether hospitality marketing communication should use AI-generated images for commercial purposes and what the consumer's reactions are towards companies employing such practices. Second, since boundary conditions seem to be crucial in shaping this impact (Arango et al., 2023; Chan, 2024), and based on the assumptions of Fluency Processing Theory (Reber et al., 2004), our research clarifies the potential moderating influence of two widely known factors in marketing literature, however unexplored in the field of generative AI perceptions: the utilitarian vs. hedonic nature of the service, and the level of customer involvement. We also explore the interaction between these factors, analyzing a potential triple interaction effect. This interaction is particularly interesting since it raises the question of whether AI-generated content requires either the consumer's low-involvement or utilitarian-focused decision-making (or both), a novel aspect that has not been explored in previous research. Third, a second qualitative study elucidates the reasons for these effects to occur. The study contributes to a better understanding of why customers assess real and AI-generated images differently and what their inferences are about the reasons that lead service providers to employ such visual content for commercial purposes. Finally, the discussion of findings leads to a set of managerial implications that should be considered as basic practical guidelines to facilitate practitioners' decision-making regarding whether and in which circumstances they should employ AI-generated images or real images.

The organization of the remaining sections of this manuscript is as follows. First, the literature review and the formulation of the research hypotheses sections are presented. The next section presents the experimental study, including the methodology and results. This is followed by a second study, of qualitative nature, which helps understand the reasons why images created by generative AI have different commercial effectiveness than real images. The final section addresses the discussion, implications for management, limitations, and future directions.

2. Literature review

In this section, we first outline the overall opportunities and threats associated with the use of AI-generated images for commercial purposes. Following this descriptive overview, we present the theoretical rationale underlying our research. Specifically, we contribute to expanding the knowledge about the Processing Fluency Theory (Reber et al., 2004) by examining how consumers process and respond differently to AI-generated versus real images used in hospitality services, a novel and underexplored context for research. In doing so, we identify and elaborate on the two key boundary conditions (i.e., utilitarian/hedonic value, and the level of consumer involvement) that may influence consumers' processing and responses to both types of images.

2.1. Use of AI-generated images for commercial purposes: opportunities and threats

Generative AI is based on deep learning models that use large amounts of data to train neural networks capable of generating new and original content (Fui-Hoon Nah et al., 2023). Advertising agencies are widely adopting tools such as ChatGPT and Midjourney to produce new content in the form of text, images, and audio, or a combination of these (De Cremer et al., 2023). Generative AI is being rapidly integrated into various applications to improve customer experience and personalize services (Chaisatitkul et al., 2024; Lee and Kim, 2024). Recent studies highlight that creative AI technologies can generate significant opportunities in how ads are conceived, produced, edited, and targeted, enabling extreme automation (Campbell et al., 2022). In addition, recent developments in generative AI enable brands to automate the entire content creation process, from audience analysis to actual content ideation and design (Brüns & Meißner, 2024). For example, some companies are using AI-based virtual influencers, such as the popular Lil Miquela (IG @lilmiquela) and Shudu (IG @shudu.gram), to promote their products and services to wider and more diverse audiences (Sands et al., 2022).

Given the impossibility of covering the breadth of formats created by generative AI, this paper focuses specifically on the advantageous potential of using AI-generated images for commercial purposes and then discusses their opportunities and threats. AI-generated images can be produced quickly and at a lower cost than traditional methods, allowing the creation of experimental stimuli without the need for extensive programming skills, making it accessible to a wider range of users (Zamudio et al., 2025). Generative AI enables the creation of highly personalized marketing content that appeals more to individual consumers, improving engagement and conversion rates (Kshetri et al., 2024). On the other hand, AI-generated images facilitate the development of novel and interactive marketing materials. By integrating alternative perception systems, companies can create unique brand personas that are difficult for competitors to replicate, thus gaining a competitive advantage (Cui et al., 2024). In this context, Epstein et al. (2023) highlight that AI-generated images can be used to enhance the promotion of services; these images are not only visually appealing but can also be customized to suit the specific aims of the brand and target audience. This allows companies to create more effective and visually appealing marketing campaigns by harnessing the flexibility and power of generative AI. In addition, the generation of synthetic images allows companies to create on-demand images without the need for expensive photo shoots. Some agencies, such as the company Generated Photos, allow brands to reuse humanoid models indistinguishable from real human models, saving significantly on professional photographers, models, and other logistical aspects (Arango et al., 2023; Campbell et al., 2022; Whittaker et al., 2020). Table 1 shows the main opportunities that image-generative AI can bring in its use in marketing.

On the other hand, companies are increasingly concerned about how consumers perceive AI-generated content. In this regard, previous scientific work has identified a notable reluctance among users to accept AI technologies, which may also extend to AI-generated images. AI-generated images often face skepticism regarding their authenticity and trustworthiness (Bui et al., 2024). For example, in the context of online reviews, consumers perceive AI-generated content as less useful, reliable, and authentic compared to human-generated content, regardless of the validity of the review or the reviewer's credentials (Amos & Zhang, 2024). Many consumers express concerns about the authenticity and moral implications of AI-generated content. They may perceive these images as less genuine than those created by humans, leading to skepticism about the ethical considerations involved in the use of AI in creative fields (Belanche et al., 2024a).

Previous literature also indicates that AI-generated image-based ads may be perceived as fake, which could negatively affect ad effectiveness (Campbell et al., 2022). Indeed, some deepfake news creation techniques represent a new level in the evolution of content creation, using AI to edit content that seems to be real but is, in fact, fictional (Arango et al., 2023; Campbell et al., 2022). This raises important ethical issues and challenges in how companies should address customers with this content (Ferraro et al., 2024; Whittaker et al., 2020). Organizations that have used AI-generated images have been criticized for pretending to be real, as was the case with Amnesty International's campaign featuring AI-generated images of the protests in Colombia (The Guardian, 2023). Such examples reflect the concerns shown in previous literature about the need to balance technological innovation with the preservation of authenticity and human creativity (Epstein et al., 2023; Fui-Hoon Nah et al., 2023). Table 2 depicts the main threats that image-generative AI poses in its application to marketing.

Table 1
Opportunities of AI imagery for marketing.

Authors	Opportunities identified
Brüns and Meißner (2024)	It automates content creation, from audience analysis to design, enabling high-quality, personalized, multi-modal content at scale. It improves consumer engagement, reinforces brand design language, and reduces production costs.
Lee and Kim (2024)	It leverages big data to understand customer preferences, enabling innovative product offerings. It enables brands to meet changing market demands and optimize design processes effectively.
Arango et al. (2023)	The realism of AI-generated images, almost indistinguishable from the real thing, can improve the effectiveness of marketing actions by inducing belief in their authenticity and creativity. This capability democratizes content creation, making it accessible and affordable for all types of marketing strategies.
Epstein et al. (2023)	The adaptability of AI-generated content ensures that promotional materials are relevant and appealing to the target audience. Images can significantly enhance the promotion of services by offering customizable images tailored to specific brand needs.
Fui-Hoon Nah et al. (2023)	Generative AI improves content generation and customer engagement. It supports the production of narrative and multimedia content, enabling companies to target potential consumers more effectively and efficiently.
Campbell et al. (2022)	It automates creative processes in ad management and quickly changes ads, models, products, and other settings, allowing the efficient creation of multiple versions of ads. It also improves effectiveness by allowing you to target specific consumer segments with personalized content.

Table 2
Threats of AI imagery for marketing.

Authors	Threats identified
Lee and Kim (2024)	Image design can create a perception of a lack of authenticity and quality, leading consumers to prefer human designs. This discrepancy may result in lower perceptions of authenticity and lower consumer trust in AI-generated products.
Arango et al. (2023)	The potential for images to be misused to spread misinformation or manipulate public opinion raises ethical and trust issues and highlights the need for ethical guidelines and transparency in content creation.
Brynjolfsson et al. (2023)	Generative AI faces significant obstacles in real-world applications, where problem types are broader and less predictable than in controlled environments. In addition, popular tools such as ChatGPT can produce false or misleading information in unpredictable ways, raising questions about their reliability in high-risk situations.
Epstein et al. (2023)	Balancing technological innovation with the preservation of human authenticity and creativity is crucial, which means ensuring that AI supports human creativity rather than replacing it, in order to maintain ethical standards.
Campbell et al. (2022)	The use of AI-generated images can create a perception of falsehood in advertisements, which can reduce their effectiveness.
Elish and Boyd (2018)	There is a risk of reducing human involvement in creative processes, leading to less authentic content. In addition, automation may replace human functions and lead to unemployment.

2.2. Processing fluency theory

Processing Fluency Theory (Reber et al., 2004) postulates that the ease with which information is processed directly influences the affective and cognitive evaluations that people make of that information. In essence, the more fluid or easy to process a stimulus is, be it visual, auditory, conceptual, etc., the more positive the judgement of that stimulus tends to be. The theory argues that this processing fluency can arise from different sources, such as familiarity or perceptual clarity, and that its impact extends not only to aesthetic perception but also influences personal beliefs, preferences, and risk judgments. Thus, Reber et al. (2004) argue that people tend to interpret ease of processing as an implicit signal of safety, familiarity, or truthfulness, which explains why easily processable stimuli tend to be evaluated more favorably.

Research in advertising has shown that information processing fluency improves self-efficacy and behavioral intentions. For instance, in pro-social campaigns, high information processing fluency increases consumers' intention to engage in behaviors such as recycling or organ donation (Kim & Jang, 2018). Higher information processing fluency also leads to more positive attitudes toward the ad and the advertised brand, as well as increased purchase intentions (Storme et al., 2015). Likewise, in e-commerce, the quality of visual information significantly affects the consumer experience, so that high perceptual fluency, achieved through clear and high-quality images, enhances the pleasure of the shopping experience and positively influences consumer behavior towards the website (Im et al., 2010). However, this theory has been scarcely applied to the processing of information generated through AI. An exception is the work of Xiao and Tan (2023), who, in the context of voice-generated virtual assistants, found that using this technology to promote new products has a negative impact on consumer acceptance. This effect is attributed to consumers' difficulties in understanding and processing generative AI recommendations due to their lack of fluency, which suggests that a similar effect may extend to the processing of AI-generated images.

2.3. Utilitarian versus hedonic value

Utilitarian and hedonic values are two fundamental dimensions of product and service value that influence consumers' purchasing behavior (Babin et al., 1994; Vieira et al., 2018). Hedonic value (Dhar & Wertenbroch, 2000; Voss et al., 2003) describes consumption experiences primarily characterized by aesthetic, sensory pleasure, fantasy, and fun. Hedonic consumption provides emotional gratification and intrinsic enjoyment. Utilitarian value, on the other hand, describes consumption experiences as primarily driven by cognitive, instrumental, and goal-oriented aspects; goods with high utilitarian value are selected for their functionality and their ability to perform practical tasks or fulfill a specific need (Dhar and Wertenbroch, 2000; Voss et al., 2003). Hedonic products appeal to sensations or experiences and are designed to provide pleasure and emotional satisfaction, whereas utilitarian products are more associated with efficiency, thus aimed at satisfying practical and functional needs (Holbrook & Hirschman, 1982). Previous studies indicate that the design and communication of products and services should consider their utilitarian and hedonic aspects to enhance customer loyalty (Chitturi et al., 2008; Dhar & Wertenbroch, 2000). Specifically, those products that satisfy the customer's utilitarian needs tend to ascertain a favorable consumer evaluation based on functionality, while those that provide hedonic benefits may lead to delight and, consequently, lead to a more extreme consumer reaction in terms of repurchase intention and WOM (Chitturi et al., 2008). Thus, in our research, we conceptualize hedonic services as those considered by consumers to have pleasure-seeking experiences —for instance, going on a summer holiday at a hotel or enjoying an ice cream in a theme park; whereas utilitarian services are those seek by the consumers for practical motivations —for instance, using a delivery service during a work meeting or having lunch in a fast-food restaurant during a short break at work.

The scarce previous literature about the use of AI for generating content incorporating hedonic or utilitarian values is unclear about its effectiveness. In this regard, Zhang et al. (2022) indicates that consumers are more willing to pay for AI-designed products when they are utilitarian rather than hedonic. Thus, in contrast to the personal view and focus of a photograph, AI lacks emotions and empathy, which challenges its ability to incorporate hedonic elements in a natural way, such as pleasure and emotions usually linked to real experiences (Belanche et al., 2024a; Longoni & Cian, 2020). However, other scholars suggest that generative AI is particularly beneficial for highlighting the hedonic value of goods, as it tends to evoke positive emotions and affect, such as generating narratives for marketing campaigns to improve consumer engagement and purchase intentions (Wen & Laporte, 2024). In contrast to this view, other authors argue that generative AI may reinforce hedonic value, for example, by evoking positive emotions, such as crafting campaign narratives that increase consumer engagement and purchase intentions (Wen & Laporte, 2024). For instance, consumer engagement and decision making can be influenced by algorithmically created text, music and advertisements (Bansal et al., 2024; Hartmann et al., 2025), or by including AI-generated thumbnails, 360° views and explanatory text (Loebbecke et al., 2024), regardless of whether consumption is hedonic or utilitarian. In turn, some studies suggest that AI-generated text, music, and advertisements can influence user engagement and decision-making, affecting both utilitarian and hedonic consumption (Bansal et al., 2024). For instance, AI-generated images used to create thumbnails can incorporate functional applications that increase utilitarian value, while also evoking emotional responses by incorporating visual cues that elicit emotional reactions (Loebbecke et al., 2024).

Due to this open debate, it is necessary to assess to what extent real or AI-generated images should be employed to promote the utilitarian or hedonic value of products and services. In this sense, according to the Processing Fluency Theory (Reber et al., 2004), the ease with which consumers can process a stimulus has a direct impact on their evaluation and attitudes towards the product. This ease of processing is enhanced for images that generate clarity in the perceptual process, as is often the case with real photographs, compared to those generated by artificial intelligence (AI), which may appear less natural and therefore require more complex processing (Reber et al., 2004). This effect may be particularly relevant when it comes to hedonic features, since their valuation is strongly influenced by the affective response derived from smooth processing (Winkielman et al., 2003). In this sense, Processing Fluency Theory posits that when a stimulus is perceived effortlessly, it tends to be evaluated with pleasure and favorably; this hedonic signal is crucial for valuing hedonic attributes, whose appeal lies precisely in offering enjoyment without cognitive load. Thus, the smooth processing of real images will be particularly favorable for evaluating hedonic services. In contrast, for utilitarian services, processing fluency may be less important as more rational and functional evaluations are taken into account in their evaluation, which may reduce the influence of processing fluency compared to hedonic products.

2.4. Level of consumer involvement with the product or service

Consumer involvement with the purchased product or service is defined as 'consumers' enduring perceptions of the importance of the product or service being evaluated, based on their inherent needs, values, and interests (Zaichkowsky, 1985). Thus, involvement refers to the intrinsic importance, personal meaning, and significant consequences that an issue has for an individual (Petty et al., 1983). This concept is paramount in consumer behavior and communication research as it affects the depth, complexity, and extent of cognitive and behavioral processes during the consumer choice process (Houston, 1978; Laurent & Kapferer, 1985). In high-involvement decision-making, consumers tend to seek more information and process both positive and negative aspects in a more extensive and complex manner (Fazio, 1990). From a marketing communication perspective (Asadollahi et al., 2011), consumers in high-involvement purchase situations allocate more cognitive attention and resources when evaluating information, enabling them to process it critically and form enduring attitudes toward the advertised brand (Belanche et al., 2017). In contrast, in low-involvement decisions, consumers do not actively seek information or comprehensively compare product alternatives, and are characterized by a perception of similarity between different brands and a lack of a specific preference for a particular one. In other words, consumers with low-involvement consider the purchase decision to be irrelevant to their lives, so they process information superficially, and renounce evaluating commercial arguments and counterarguments with depth (Ha & McCann, 2008; MacInnis & Park, 1991). It is important to note that the same product or service may be used for highly and lowly involvement situations depending on whether the consumer assumes that the decision related to that product is important or unimportant (e.g., a lunch in a restaurant, Bambauer-Sachse & Rabeson, 2015; or a stay in a hotel, Casidy et al., 2018). Consequently, in our research, we conceptualize highly involved consumers' decisions as those perceived as important —for instance, taking hospitality decisions with important implications for others, such as deciding the lunch for an important work event or the hotel to spend holidays for family or friends (Bambauer-Sachse & Rabeson, 2015). In turn, low-involvement consumer decisions are those perceived as unimportant —for instance, having something to eat in a work break or stopping in a kiosk to have an ice cream during holidays.

Previous literature suggests that when consumers face highly involved purchase decisions, the presence of AI in content creation primarily impacts consumers' perceptions of the message's authenticity and credibility (Brüns & Meißner, 2024). For example, generative AI is employed to promote high-involvement artistic intangible goods, such as music; however, this approach is less effective for tangible products, where AI reduces quality perceptions (Moura & Hindley, 2023). Consumers tend to rate AI-generated content less favorably when they are aware of its synthetic nature (Arango et al., 2023). In this sense, consumers' level of involvement may determine their critical evaluation and approval or disapproval of companies using AI-generated commercial images (Vafeiadis et al., 2019).

As discussed above, AI-generated images are generally more difficult to process than real images. In high-involvement situations—where consumers engage in more elaborate and attentive information processing (Petty et al., 1983; Zaichkowsky, 1985)—processing fluency becomes particularly important, as any doubt about the veracity of the content or cognitive friction may trigger distrust or skepticism (Arango et al., 2023; Belanche et al., 2017). In this context, real images, which are typically easier to process due to their authenticity, realism, and familiarity, are likely to be evaluated more favorably than AI-generated images, which are often perceived as synthetic or inauthentic and require more cognitive effort to interpret (Arango et al., 2023; Vafeiadis et al., 2019). Conversely, in low-involvement contexts, where consumers process information more superficially (Ha & McCann, 2008; MacInnis & Park, 1991), the role of fluency may be less critical, potentially diminishing the difference in consumer responses to AI-generated versus real images.

3. Hypothesis formulation

Consumers' perceptions and attributions regarding image authenticity can vary greatly between AI-generated images and real images (Brüns & Meißner, 2024; Chaisatitkul et al., 2024). The most general research stream in this field indicates that real images can be perceived as more authentic and trustworthy, positively influencing usage intention and service recommendation (Arango et al., 2023; Brüns & Meißner, 2024; Lee & Kim, 2024). In turn, images created with generative AI create uncertainty about the verisimilitude of the content and erode reliability, resulting in rejection and reduced commercial effectiveness of AI-generated content (Arango et al., 2023). The introduction of potential bias in the images due to the AI creation method and the lack of human involvement in the creative process (Belanche et al., 2024a) may result in customer avoidance of such products or services. Dwivedi et al. (2023) note that, although AI technologies can produce content of similar quality to that produced by a professional photographer, the authenticity perceived by consumers is critical to the acceptance and use of the service. Specifically, the mere perception of falsehood in AI-generated content could negatively affect the effectiveness of the advertisement and consumer trust (Campbell et al., 2022). In this regard, Lee and Kim (2024) study shows how consumers evaluated human-generated fashion designs more favorably than AI-generated ones, due to the perception of higher authenticity and expected product quality when created by humans.

In addition, while AI-generated images may show outstanding aesthetic quality, they can also evoke perceptual dissonance if users perceive them as inauthentic or too artificial, thereby affecting processing fluency (Reber et al., 2004). In advertising, AI-generated content is often perceived as insincere or even fake, negatively impacting perceptions of sincerity and realism (Aljarah et al., 2024). Images created with AI are often seen as less authentic and admired, especially when AI is actively involved in the creative process (Messer, 2024). Therefore, according to Processing Fluency Theory, consumers will have negative perceptions when processing an AI-created image and will therefore avoid using the service promoted in the picture or will not recommend it to others, compared to a real image that will be more easily processed. Based on these arguments, the following hypothesis is proposed:

Hypothesis 1. *. Compared to real images, images created by generative AI reduce (H1a) intention to use the service and (H1b) intention to recommend the service.*

Previous literature on hedonic and utilitarian dimensions suggests how visually presented products and services can significantly influence consumer perception (Voss et al., 2003). Consumers place more value on commercial images because they need to justify hedonic consumption, which is considered more indulgent and dispensable than utilitarian consumption (Okada, 2005). Visual presentation is also particularly relevant for hedonic services, as they are often evaluated subjectively and affectively (Chitturi et al., 2008; Dhar and Wertenbroch, 2000). In this sense, a recent study on human and virtual influencers (Belanche et al., 2024b) showed that customers of hedonic services highly value content authenticity, human and personal touch, and their ability to generate empathy. In this context, AI-generated images may be diminished in their ability to convey emotions effectively, as they do not generate the identification and empathy generated by human-created content (Belanche et al., 2024b). Thus, consumers tend to prefer human recommendations for hedonic services due to their ability to generate stronger emotional responses and facilitate self-referral to their own emotional needs and personal enjoyment (Wien & Peluso, 2021). In turn, for utilitarian services, where functionality is more important than emotions, the use of AI-generated images may be less relevant, as consumers are more focused on the efficiency and effectiveness of the service. Longoni and Cian (2020) argue that, in utilitarian contexts, consumers may even prefer AI-based recommendations due to the perception that these are more accurate and objective. Belanche et al. (2024b) also argue that, when it comes to utilitarian services, where functionality and efficiency are the main evaluation criteria, AI can be equally effective or even preferred since originality and empathy are less relevant in utilitarian services than in hedonic ones.

In this regard, Processing Fluency Theory, Reber et al. (2004), suggests that the ease with which a stimulus is processed can increase hedonic pleasure. This is supported by findings that images processed more fluently are the most liked, as shown by studies manipulating perceptual fluency through subliminal priming and presentation duration (Forster et al., 2013). Therefore, considering that real images are processed more fluently than AI-generated ones, content identified as artificial or showing clues of falsity (Amos & Zhang, 2024; Gross, 2024) will generate a negative emotional response linked to disorientation and discomfort (Denson, 2023), that will decrease the hedonic value of the consumption experience.

Finally, Okada (2005) and Voss et al. (2003) highlight that consumers are more likely to recommend services that they perceive as emotionally satisfying and visually appealing as a kind of anticipation of pleasure enactment. Hedonic services are highly dependent on the perception of the quality of the experience and the emotions expected to be obtained, so the negative impact of AI on the intention to use and recommend will be even greater for hedonic services. Therefore, the following hypothesis is formulated:

Hypothesis 2. *Service type moderates* Hypothesis 1*, such that the* ***negative*** *influence of images created with generative AI will be greater for hedonic services than for utilitarian services in terms of (H2a) intention to use the service and (H2b) intention to recommend the service.*

Existing literature suggests that images used in marketing communication can influence consumers differently depending on their level of involvement; in high-involvement situations, consumers tend to process information more extensively, deeply, and critically (Petty et al., 1983). This means that high-involvement consumers are more sensitive to the characteristics and attributes of the product or service, so that the authenticity of the images could have a stronger impact on their decisions. Thus, highly involved customers are more likely to question the authenticity and manipulative use of AI-generated images, which could lead them to doubt the veracity of the representation of the service.

Highly involved consumers tend to be more critical and more suspicious of the commercial information they process (Celsi & Olson, 1988; Petty et al., 1983) and tend to evaluate arguments and counterarguments in more detail (Wright, 1973), which in practice means that they are more aware and critical of the possible disadvantages or shortcomings of a product or service presented in an AI-generated image. This inherent skepticism may lead to a negative evaluation of the information provided through these images, as they consider them to be an inaccurate representation of the service (Brüns & Meißner, 2024). In this regard, previous literature on AI virtual assistants has found that customers facing high-involvement decisions tend to distrust AI voice recommendations and require real product images to make a purchasing decision (Hari et al., 2024).

In this sense, the Processing Fluency Theory (Reber et al., 2004) suggests that the ease with which information is processed influences both affective and cognitive evaluations (Min, 2022). Therefore, in high-involvement shopping situations where consumers need to process information more deeply (Zaichkowsky, 1985), the fluidity of image processing becomes particularly relevant, and in this sense, it is real images that are processed more quickly and clearly (Vafeiadis et al., 2019), so that the consumer will prefer a real image to an AI-generated image. In the case of a low-involvement shopping context, where the need for information is much lower (Ha & McCann, 2008), whether an image is easier or harder to process will matter less; therefore, the consumer may be more indifferent between a real or an AI-generated image. Thus, given that highly involved consumers are more likely to process visual information critically, AI-generated images are likely to have a more significant negative impact on their intention to use and recommend the service (Petty et al., 1983; Zaichkowsky, 1985). In contrast, in low-involvement situations, consumers do not spend as much effort evaluating information (Petty et al., 1983), implying that they are less likely to question the authenticity and reliability of images, and that therefore, the use of AI-generated images would have less impact on their perceptions and decisions about a product or service. Accordingly, the following hypothesis of this paper is formulated:

Hypothesis 3. *The level of involvement moderates* Hypothesis 1*, such that the* ***negative*** *influence of images created with generative AI will be greater in high-involvement than in low-involvement decisions, in terms of (H3a) intention to use the service and (H3b) intention to recommend the service.*

The research model is displayed in Fig. 1.

4. Study 1: experimental study

4.1. Method

4.1.1. Data collection and sample

To test the proposed hypotheses, an online experiment was conducted targeting potential consumers of restaurant and hospitality services. The data was collected through a non-probabilistic convenience and snowball sampling. Following this approach, the experiment and subsequent questionnaire were distributed within the university community in Spain during the second quarter of 2024. The link to the study was shared by students and members of the academic community through their personal networks, primarily on Instagram. The reason behind using Instagram is that this social network seems to be particularly suitable for our target sample (Ballester et al., 2023; Roozen, 2023). Despite convenience sampling offers less generalizability compared to probability sampling (Jager et al., 2017), it enables the collection of a relatively homogeneous sample and is considered appropriate for exploratory research, particularly when the data collected are relevant to the research questions being addressed, as it is the case (Etikan et al., 2016; Tukey, 1977).

In the welcoming message, participants were notified about the scientific purposes of the study. Then, in the first part of the study, a hypothetical scenario was presented to participants, accompanied by images corresponding to a service, for which they would later answer a series of questions (e.g., intention to use the service) in a structured questionnaire. To measure the study variables, the questionnaire included 7-item Likert-type and semantic differential multi-item scales adapted from the existing literature. Specifically, the experiment employs a $2 \times 2 \times 2$ between-subjects design with random assignment, resulting in a balanced distribution of participants across scenarios, as shown in Table 3. The final stimuli or treatments resulting from the combination of these manipulations yielded eight versions of the scenarios, which were randomly presented to participants. Specifically, the manipulations carried out were the type of image presented in each scenario (real image or AI-generated image), the type of service

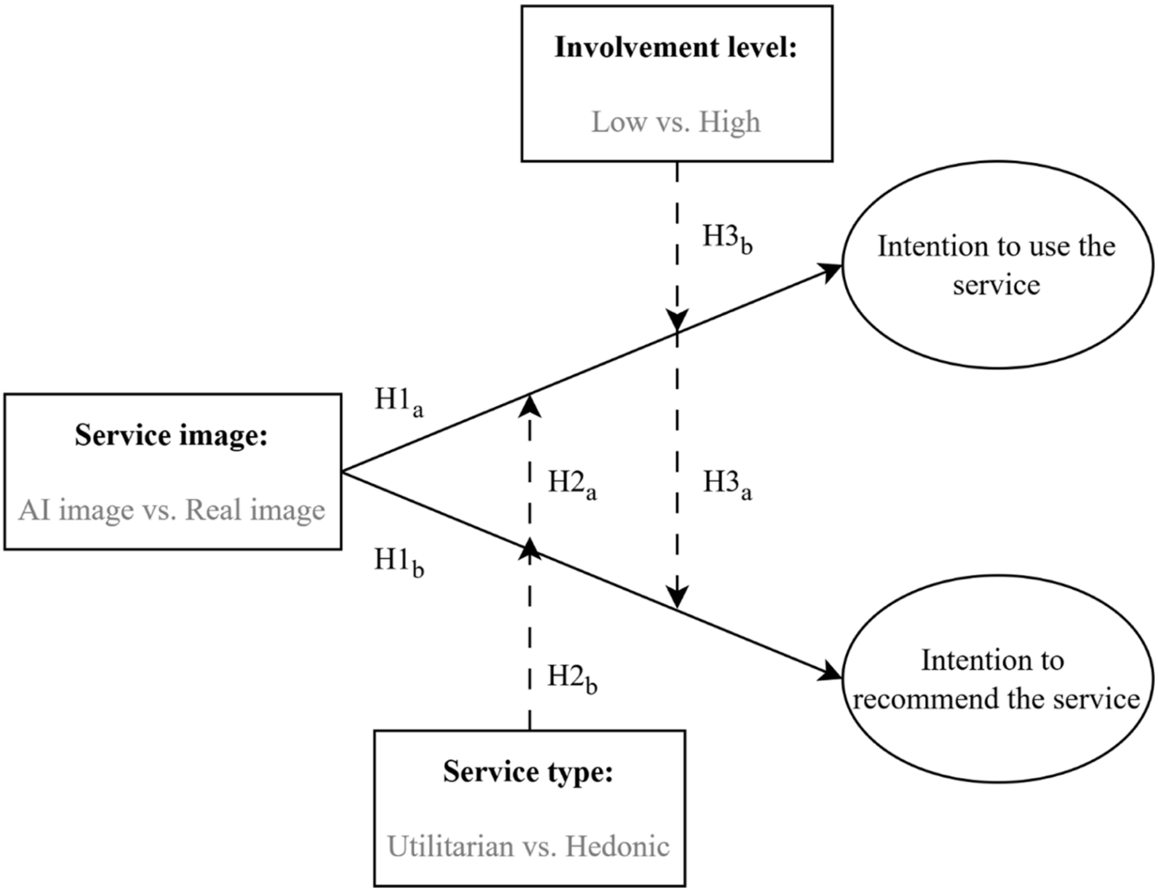

Fig. 1. Research model.

Table 3
Number of participants per scenario.

	Utilitarian service	Hedonic service
High-involvement	AI-generated image (N = 43)	AI-generated image (N = 40)
	Real image (N = 42)	Real image (N = 41)
Low-involvement	AI-generated image (N = 42)	AI-generated image (N = 42)
	Real image (N = 45)	Real image (N = 43)

(hedonic or utilitarian) and the level of involvement required by the scenario (high-involvement or low-involvement). Real images were sourced from the Internet by searching for authentic photographs of hospitality services (e.g., hotels, restaurants). Corresponding AI-generated images were then created using DALL-E through multiple iterations, aiming to closely replicate the content and composition of the real-image counterpart (see Appendix I). Manipulations of the service type and involvement level were performed using different texts following the guidelines of previous literature (e.g., Belanche et al., 2024b; Casidy et al., 2018; Hassan & Casaló Ariño, 2016), as detailed in Appendix I. In particular, we used specific hospitality-related scenarios to manipulate these variables, aiming to present situations that were realistic and familiar to participants and that could be clearly distinguished as highly or lowly involving, as well as hedonic or utilitarian. More precisely, as described in Appendix I, service type scenarios were differentiated based on the underlying consumption goals: hedonic pleasure-seeking experiences (e.g., *"you want to enjoy the experience, be at ease in the place, savor the ice cream, cool off, and hang out"*) and utilitarian practical motivations (e.g., *"your idea is to make it quick, efficient and practical"*). Similarly, to manipulate involvement, we varied the perceived importance and consequences of the decision, which make consumers to be highly or lowly involved with the decision by presenting them with important (e.g., *"you have been given the important task of choosing the hotel for the week's holiday"*) or unimportant hospitality related decisions (e.g., *"Lunch is not important today [...], it is an inconsequential decision"*). These manipulations are consistent with theoretical definitions and previous experimental designs manipulating involvement in this area (e.g., a lunch in a restaurant, Bambauer-Sachse & Rabeson, 2015; or a stay in a hotel, Casidy et al., 2018).

Since the questionnaire was administered in Spanish, all materials and the original English items were translated into Spanish and then double-back-translated following the collaborative and iterative translation procedure proposed by Douglas and Craig (2007). First, two bilingual researchers independently translated the materials into Spanish, and any discrepancies were resolved in a joint review with a third reviewer. Then, a small group of bilingual participants then reviewed the final version and provided feedback, ensuring clarity and semantic accuracy (e.g., Diallo, 2012).

Regarding the sample, after discarding incomplete questionnaires and questionnaires with inconsistent responses (e.g., responses to all items with a value of 1), we obtained a sample of 338 participants, which surpassed the minimum sample size of 300 recommended by GPower, assuming a medium effect size ($f = 0.25$; Cohen, 1988), significance level $\alpha = .05$, and power $(1 - \beta) = .90$ (Hou et al., 2024). The sample was composed of 50.9 % males, with 41.1 % aged between 25 and 34 years, and 76.3 % holding a university degree. In addition, they were asked how often they used generative AI (never 25.7 %, almost never 37.3 %, several times a month 25.7 %, several times a week 8.6 %, several times a day 2.7 %).

4.1.2. Validation of measurement scales

First, to ensure content validity, the scales used were borrowed from previous literature and adapted to the specific context of this research.

Specifically, the product type scale (hedonic vs. utilitarian) was adapted from Hassan and Casaló Ariño (2016) and employs a semantic differential scale from 1 to 7. The level of involvement was measured using Zaichkowsky's (1985) scale. Concerning the dependent variables, the Bhattacherjee (2000) behavioral intention scale was used to assess the intention to use the promoted service, and finally, the Harrison-Walker (2001) positive WOM scale was adapted to measure the intention to recommend the service. All the scales are included in Appendix 2.

Second, Cronbach's alpha was used as a measure of internal consistency as it indicates the degree to which the items of a scale are correlated with each other, and the values obtained for all scales (product category $\alpha = 0.955$, level of involvement $\alpha = 0.947$, intention to use $\alpha = 0.974$, intention to recommend $\alpha = 0.965$) suggest good internal consistency.

4.2. Manipulation checks

First, it was verified that the participants had seen the image and correctly considered it as real or created with generative AI, depending on the assigned scenario. In fact, to facilitate the correct identification of the image, in the scenarios that showed an image created with AI, the label "Image created with generative AI" was included. It was confirmed that all valid participants correctly identified the type of image presented in the assigned scenario, differentiating between images created by generative AI and real images. This verification was performed using the question: "The image seen in the initial scenario was: an image created by generative AI or a real image," posed at the end of the survey to prevent the question itself from influencing participants' perceptions and responses.

Second, the scale developed by Hassan and Casaló Ariño (2016) to measure hedonic-utilitarian value was employed to check the service type. The mean comparison revealed that hedonic scenarios show significantly higher values on the scale than utilitarian ones, $M_{Hedonic} = 6.02$, $M_{Utilitarian} = 1.68$, $t(336) = 35.54$, $p < 0.01$, confirming that participants clearly distinguished between hedonic and utilitarian services.

Finally, to check the manipulation of participants' level of involvement, we used the involvement scale adapted from Zaichkowsky (1985). The results of the test indicated that participants in the high-involvement scenarios perceived the decision as significantly more important than those in the low-involvement scenarios (MHigh--Involvement = 6.23; MLow-Involvement = 3.28; t(267,85) = 20.81, $p < 0.01$).

4.3. Results

In order to evaluate the differences in the proposed variables between the different scenarios proposed, an analysis of variance (ANOVA) was carried out, one for each dependent variable, with the objective of evaluating the effect of the type of image (generated by AI or real), the type of service (hedonic or utilitarian) and the level of involvement (high or low) on the dependent variables use and recommendation intentions.

Hypothesis H1a stated that the use of an image created by generative AI would reduce intention to use compared to the use of a real image. ANOVA results confirmed this hypothesis. Specifically, a significant difference was observed between usage intentions for images created by generative AI and those created by real AI ($F(1, 337) = 151.53$, $p < 0.01$, $\eta^2 = 0.316$). Mean values indicated that AI-generated images have a lower intention to use (MAIImage = 3.02) compared to real images (MRealImage = 5.26), which was further supported by a *t*-test (t (320,02) = -11.94, $p < 0.01$). Complementarily, hypothesis H1b postulated that the use of a generative AI-created image would reduce recommendation intention compared to the use of a real image. This hypothesis was also confirmed by the ANOVA results ($F(1, 337) = 173.82$, $p < 0.01$, $\eta^2 = 0.346$). Mean values showed that AI-generated images elicit lower recommendation intention (MAIImage = 2.73) versus real images (MRealImage = 4.84), which was also confirmed by a *t*-test (t(325,11) = -12.54, $p < 0.01$). Gender and age were included as control variables in the analyses, but their effects on intention to use and intention to recommend were not significant ($p > 0.10$).

Regarding moderation effects, hypothesis H2a suggested that the negative influence of the use of images created with generative AI on intention to use would be greater for hedonic services than for utilitarian services. The results of the analysis supported this hypothesis ($F(1, 337) = 7.98$, $p < 0.01$, $\eta^2 = 0.024$), indicating that service type moderates the relationship between image type and intention to use, with this relationship being more pronounced for hedonic services. Fig. 2 shows these effects. Similarly, hypothesis H2b posited that the influence of using images created with generative AI on recommendation intention would be greater for hedonic services compared to utilitarian services. The data supported this hypothesis ($F(1, 337) = 7.26$, $p < 0.01$, $\eta^2 = 0.022$), confirming that the impact of AI-generated images on recommendation intention is more pronounced in the context of hedonic services. Fig. 2 shows the effects just mentioned.

On the other hand, hypothesis H3a proposed that the negative influence of using images created with generative AI on intention to use would be greater for high-involvement services compared to low-involvement services. This assumption was validated by the analysis performed ($F(1, 337) = 8.28$, $p < 0.01$, $\eta^2 = 0.025$), indicating a significant moderation of the level of involvement in the relationship studied. Fig. 3 shows the aforementioned effect. Finally, hypothesis H3b stated that the influence of the use of images created with generative AI on recommendation intention would be even more negative for high vs. low-involvement services. The results confirmed this hypothesis ($F(1, 337) = 11.41$, $p < 0.01$, $\eta^2 = 0.034$), confirming that service involvement is also an important moderator in the effect of AI-generated images on recommendation intention. These effects can be seen in Fig. 3.

The adjusted R^2 values show that the models explain a considerable proportion of the variance in purchase intention (adjusted $R^2 = 0.35$) and recommendation intention (adjusted $R^2 = 0.39$), which underlines the relevance of the investigated factors in customers' decisions regarding AI-generated images in commercial communication.

4.4. Post-hoc analysis: triple interaction effect

Additionally, a post-hoc analysis was conducted to assess the potential simultaneous interaction of the three independent factors on the dependent variables. The results revealed a significant triple interaction effect between image type, service type, and level of involvement on both intention to use ($F(1, 337) = 7.37$, $p < 0.01$, $\eta^2 = 0.023$) and intention to recommend ($F(1, 337) = 9.88$, $p < 0.01$, $\eta^2 = 0.015$). This three-way interaction suggests that the combination of these three factors has a complex and significant impact on customers' decisions. Figs. 4 and 5 show the differences between hedonic and utilitarian scenarios, respectively, in terms of intention to use, while Figs. 6 and 7 show the differences in intention to recommend for the hedonic and utilitarian scenarios, respectively.

In the context of hedonic services, the use of AI-generated images significantly decreases the intention to use the service compared to the use of real images. This effect is consistent for both high-involvement and low-involvement services, indicating that, regardless of the level of customer involvement, services that provide pleasure or enjoyment (hedonic) are perceived less favorably when using AI-generated images. For utilitarian services, the situation is different; in this case, the reduction in purchase intention due to the use of AI-generated images compared to real images is only significant when the service is of high customer involvement. In low-involvement scenarios, the impact of the type of image (AI-generated or real) on purchase intention is irrelevant, suggesting that consumers do not perceive a considerable difference between the use of an image of one type or the other when it is a utilitarian service that is not important to them. These findings are relevant

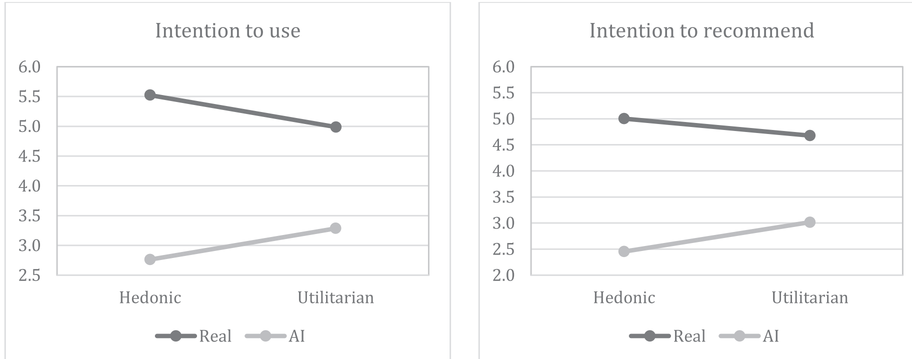

Fig. 2. Interaction effect between the type of photo and service category on the intention to use and intention to recommend.

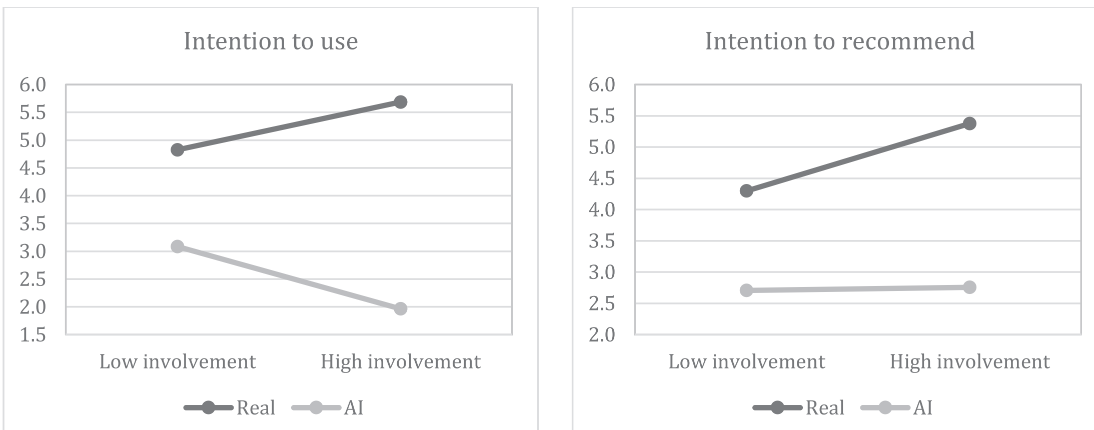

Fig. 3. Interaction effect between the type of photo and the level of involvement on the intention to use and intention to recommend.

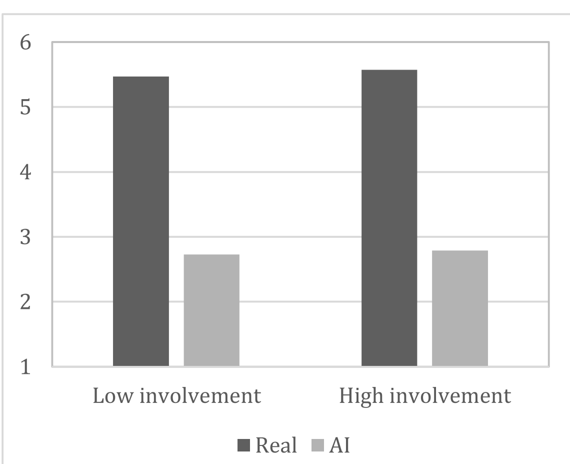

Fig. 4. Intention to use, hedonic service conditions.

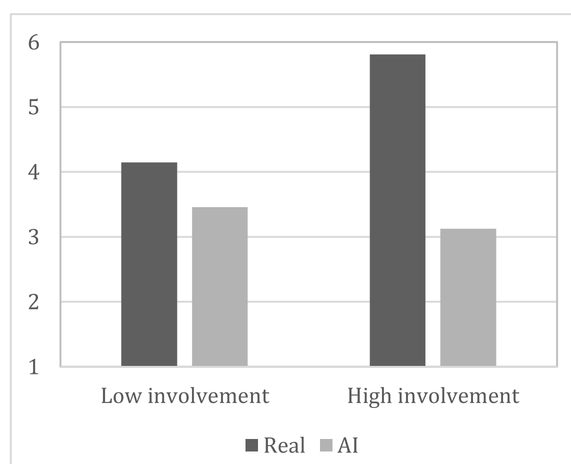

Fig. 5. Intention to use, utilitarian service conditions.

as they demonstrate that consumers' perception and intention are influenced not only by the type of image used but also by the type of service and the level of involvement simultaneously. Therefore, the results highlight the importance of considering these factors together when designing marketing and communication strategies.

5. Study 2: qualitative study

Numerous scholars are calling for mixed-methods research, that is, combining qualitative research to build upon and enrich quantitative findings (Maier et al., 2023; Venkatest et al., 2023). In response to this call and assuming the novelty of using AI-generated images in marketing communication, this research conducts a qualitative study to

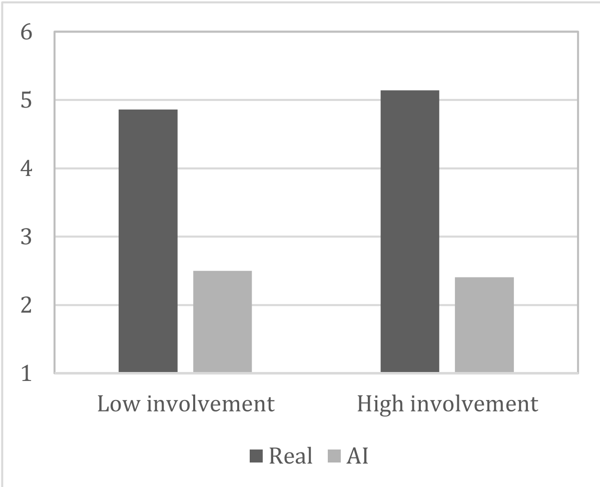

Fig. 6. Intention to recommend, hedonic service conditions.

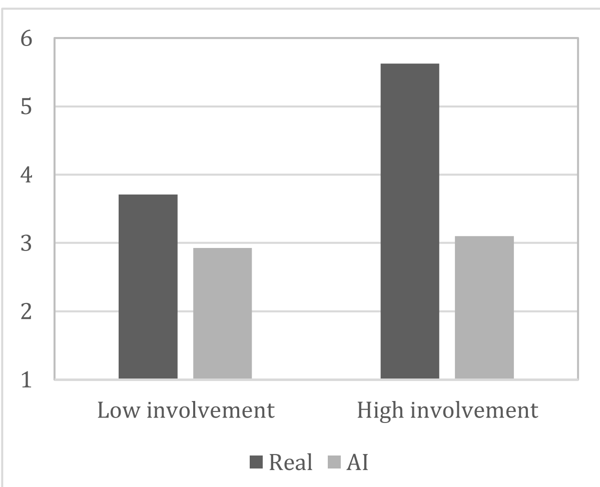

Fig. 7. Intention to recommend, utilitarian service conditions.

complement and further understand the findings of the previous investigation. Qualitative research enables the exploration of issues from the participants' perspectives, providing valuable insights into the meanings they ascribe to their own perceptions and experiences (Hennink et al., 2020). The qualitative approach is chosen for this study due to its interpretive nature, which is particularly well-suited at this stage of the investigation, where our aim is to deepen our understanding of the phenomenon under research. Thus, this qualitative study examines the participants' thoughts on their varying willingness to use or recommend a service based on the scenarios presented in the initial study. This qualitative approach ensures a deeper comprehension of the factors underlying the observed results.

5.1. Method

Accordingly, an online qualitative survey with open-ended questions was employed (Braun et al., 2021). This approach involves asking all participants the same set of open-ended questions in the same order, ensuring consistency. The sample was recruited through a prestigious online consumer panel in Spain, utilizing a non-probabilistic purposive sampling method that targeted potential consumers of restaurants and hospitality services. The present method was employed to enhance accessibility, geographic reach, and comfort for the panel participants (Braun et al., 2021). The final sample consisted of 60 participants. The sample consisted predominantly of men (61.7 % men, 36.7 % women, 1.7 % non-binary), with a mean age of 32.47 years (SD = 10.79). Most participants reported having university education (76.7 %) and being employed (66.7 %) at the time of the study. Surveys were collected until the saturation criterion was reached, whereby no new thematic insights emerged (Flavián et al., 2024; Guest et al., 2006; Malterud et al., 2016).

Participants accessed the questionnaire after being informed about the scientific purposes of the study. Subsequently, they completed the consent form. Following a between-subjects design, each participant was randomly assigned to one scenario. To ensure consistency between the two studies, the same scenarios and materials were used in the quantitative research (see Appendix 1). Thus, the same manipulations as in the first study were introduced when presenting the scenario (type of image: real vs. AI-generated; type of service: hedonic vs. utilitarian; level of involvement: high vs. low). Each of the eight scenarios was assigned to 6–10 participants. After reading their scenario, participants responded to two open-ended questions: "Would you use the service provided by this company?" and "Would you recommend the service provided by this company?". Participants were required to justify their answers. The questionnaire finished asking participants about their sociodemographic information and acknowledging their participation. As in Study 1, we followed the process proposed by Douglas and Craig (2007) to translate all the materials into Spanish.

5.2. Results

Building on grounded theory methodology (Glaser & Strauss, 1967), the approach outlined by Chaudhuri et al. (2024) was employed for the analysis. The process involved iterative cycles of data collection, memo-writing, and comparative analysis. Three independent researchers, blind to the hypotheses, experienced in qualitative research and customer experiences with new technologies, conducted the coding. Each researcher reviewed the complete transcripts independently, taking detailed notes to identify emerging concepts related to participants' perceptions and behaviors (Corbin & Strauss, 1990). Regular meetings were held to discuss the findings, reconcile discrepancies, and reach consensus on themes and categories. The researchers revisited the transcripts repeatedly until theoretical saturation was achieved.

First, in relation to the proposed hypotheses, this study reveals clear distinctions in participants' preferences based on the type of image, the nature of the service, and the level of involvement in the decision-making process. Table 4 presents the results across these conditions and includes verbatim quotes that exemplify and further support the findings of Study 1. More precisely, the results of the study demonstrate a marked preference for real images over AI-generated ones, particularly in contexts involving hedonic services or high-involvement decisions. Participants highlighted the realism and accuracy of real images, which they perceived as providing a precise representation of the service, thereby enhancing their decision-making process. In contrast, while real images were still preferred for hedonic services, some participants considered AI-generated images acceptable for simpler, functional decisions. Similarly, the negative impact of AI-generated images appeared less pronounced in low-involvement scenarios, where the lower importance of the decision diminished the importance of offering real images.

In addition to confirming the research hypotheses, the qualitative analyses also contribute to clarifying customers' perceptions and the underlying reasoning behind their rejection of service providers using AI-generated images for commercial purposes. Specifically, three main themes were identified from the transcriptions, as detailed below.

5.2.1. Distrust

One of the main barriers for customers to accept and be persuaded by commercial AI-generated is "perceived distrust". This topic includes participants' skepticism and concerns regarding the service

Table 4
Participants' responses across the different conditions.

Conditions	Verbatim quotes
Type of image: Real vs. AI-generated	*"I would only use AI-generated images to create a rough draft or to compare options based on general features, but not for decision-making. I prefer to choose based on real options. I don't like relying on AI for everything: only as a tool to simplify choices or visualize conceptual ideas."* (P4) *"First, I'd like to see real photos of the service because AI-generated images might differ significantly from reality. Second, they could be misleading, and third, they don't feel realistic."* (P9) *"Yes, I will use the services of this company because, by using a real image, it gives me a more accurate idea of how they actually operate. Other companies don't publish such images, making it harder to form a clear impression."* (P52).
Type of service: Hedonic vs. Utilitarian	*"If you're looking for a more realistic and enjoyable experience, you don't want to see a heavily edited AI image."* (P10). *"I think AI-generated images may be enough because they show everything needed for a quick and practical meal that doesn't take long to prepare, like a burger or a sandwich."* (P42).
Level of involvement: High vs. Low	*"Since it's not something very important decision, I'm not sure if using real images would influence my final choice. It's not essential."* (P18). *"If it's just to fill your stomach, the quality of the food isn't as important, so an AI-generated image would be sufficient."* (P36). *"Organizing events that include catering is quite expensive and requires significant effort. I would prefer to see real photos rather than AI-generated ones to ensure the quality of the services being hired."* (P46).

representation using AI. Three sub-themes are detected in this topic: lack of reliability, lack of professionalism, and deceptiveness.

Regarding the lack of reliability, participants frequently expressed doubts about the dependability of visual representations, particularly those generated by AI. Conversely, real images seem to align users' expectations with the actual service, so participants fairly preferred them. For instance, some participants remarked:

> *"No, I won't recommend this service because I can't determine how good or bad it might be based on AI-generated images. I also don't know how much confidence the place would inspire in me"* (P31).

> *"I would use the service because real images offer transparency and ensure that the product meets expectations"* (P40).

> *"You cannot trust a company that fails to demonstrate its service. Real photos are required. This is unacceptable"* (P48).

> *"Using real images enhances the credibility associated with the brand or company"* (P57).

Another sub-theme that emerged from the analysis is categorized as perceived lack of professionalism. This topic suggests that the reliance on AI-generated images could harm the perception of a company's professionalism. For example, some participants expressed:

> *"No, I wouldn't use this service based on the AI images. I believe it doesn't give a good image of the company"* (P20).

> *"I don't understand why a business with a good service would choose to use AI-generated images. It doesn't seem like a sensible decision to me"* (P23).

The last sub-theme in this category is deceptiveness. Participants considered the use of AI-generated images as potentially misleading, dishonest, or even malicious. Some participants associate AI use with malevolent practices, which leads them to skepticism or alarmingly attributing hidden motivations to the company's use of AI. Some examples of the participants' quotes are displayed below:

> *"Using AI-generated images would make me think I'm being deceived in some way. Additionally, the fact that they don't show their actual facilities would make me suspicious"* (P8).

> *"If they upload an AI-generated image instead of a real one, I would think they are hiding something from me"* (P22).

> *"AI-generated images cannot accurately represent a company's service. It's essential to see real photos of the service. This feels like a scam"* (P48).

These aspects are particularly relevant when they deal with high-involvement decisions and less critical in low-involvement situations:

> *"I distrust AI, so I would not invest large amounts of money in a service involving AI, particularly for this important decision"* (P9).

> *"Although using AI-generated images in this context reflects very poorly on the establishment, if it is an unimportant decision, maybe I would use it"* (P23).

5.2.2. Lack of veracity

The second category encompasses "lack of veracity/truthfulness", which captures concerns regarding the problems of authenticity in AI-generated images and their inability to accurately represent the truth of the service. This topic encompasses two distinct sub-themes: mismatch with reality and the imagination barrier.

First, the mismatch with reality is highlighted as participants frequently expressed doubts about the ability of AI-generated images to accurately represent the services. These concerns arise from a potential lack of correspondence between the visual representation in the AI-generated image and the actual service experience. Some of the respondents remarked:

> *"The service using AI images wouldn't be providing truthful information." (P1)*

> *"The images generated by AI might not correspond to reality"* (P12).

> *"I prefer the images to be real. I dislike those created by AI because they may not faithfully represent reality"* (P17).

The imagination barrier emerges due to the previous sub-theme. Participants highlighted the challenge of visualizing the actual service through AI-generated images (compared to real images). For example, the participants' responses suggest that real images not only enhance transparency but also facilitate a clearer alignment between customer expectations and the service experience:

> *"If I had different options, I would choose the service of a company that uses real photos over AI-generated images. It gives me a more accurate idea of the product being offered."* (P15).

> *"I think I would use the service, because the displayed real image shows how the service would appear in an actual setting. It helps us imagine what the service would look like."* (P55).

These aspects are particularly valued for hedonic services and are less relevant in utilitarian ones:

> *"It doesn't matter to me [that they use AI-based images] when I am only looking for a high-speed service"* (P25).

> *"The [real] image shows how the hotel facilities are, which is crucial for people going on vacation" (P41).*

5.2.3. Other aspects (miscellaneous)

The final theme, or "miscellaneous," encompasses a variety of additional factors that do not fall neatly into the previous categories but are nonetheless significant. Participants attribute the use of AI-generated images as a cost-saving strategy that detracted from the company's overall quality. For instance, some participants commented:

> *"Even if it requires additional resources, it's worth investing in doing things properly (using real images). It still makes sense and remains practical to prioritize quality"* (P32).

"I find it very unprofessional to use AI instead of hiring an artist. If they're not willing to invest in an artist, I doubt the overall quality of their service" (P33).

Another point highlighted by participants is the impersonal nature of AI-generated images. Participants consider that using this technology to design images may weaken the emotional connection between customers and the company. For example, one participant observed:

"The lack of real personalization in AI-generated images might prevent customers from identifying with the company. AI-created images can convey a sense of impersonality, which could negatively impact the emotional connection with customers" (P34).

Again, these effects are higher for those participants in hedonic versus utilitarian scenarios:

"I would not like to be the first customer of the hotel and base my holidays decision on an AI image. I will wait for more pictures showing other customers' experiences" (P13).

"I would recommend it [the service with the AI-generated image] to people who only want to eat something fast or to be prepared quickly" (P42).

6. Discussion

The advance of generative AI, particularly in image creation, has opened new possibilities for marketing and communication. The ability to create persuasive visual content through this tool is enabling companies to improve their communication strategies. However, the use of generative AI also poses several challenges (Kshetri, 2024; Mustak et al., 2023). Particularly, the introduction of these technologies has also raised concerns about their impact on consumer perception and their effectiveness for communication campaigns. Indeed, there is an ongoing debate about whether and under what circumstances AI-generated images should be used in hospitality communication (Hartmann et al., 2025; Seo et al., 2025; Sigala et al., 2024). This paper contributes to the existing literature by examining how AI-generated images, compared to real images, influence consumers' intentions to use and recommend services, and identifying the boundary conditions that practitioners should consider when deciding whether to utilize AI imagery. The findings of our studies suggest interesting theoretical and managerial implications.

6.1. Theoretical contributions

Our research is grounded in the Processing Fluency Theory (Reber et al., 2004), which posits that consumers process real or AI-generated images differently. In this regard, our work contributes to the development of these theoretical underpinnings in the novel context of utilizing generative AI for hospitality communication. We enhance our understanding of this process by focusing on consumers' reactions to companies engaging in this practice through a combination of quantitative and qualitative methods. In particular, our research reveals that the distinction between hedonic and utilitarian service value and the level of consumer involvement act as boundary conditions for this effect to occur.

Advancing on the understanding on the lights and shadows of generative AI (Campbell et al., 2022; Kietzmann et al., 2018), our research shows that while AI-generated images can be visually appealing, consumers may be more critical of these images as they are less authentic or convincing than real images, which negatively impacts their intention to use and recommend services. The present research contributes to clarifying the existing debate on the appropriateness of using AI images (Califano and Spence, 2024; Chaisatitkul et al., 2024), corroborating that consumers distrust these images and prefer real images when making behavioral decisions about a service, in line with the findings of recent studies on AI-generated product images (Brüns and Meißner, 2024; Lee and Kim, 2024). This finding is also consistent with the results of previous studies in other contexts. Consumers show lower purchase intention for financial products when they perceive that they receive information from an AI system rather than from a human (Luo et al., 2019); and readers perceive algorithm-generated news as less credible and engaging than news written by human journalists (Graefe et al., 2018). Similarly, in the field of creative content creation, Van den Broeck et al. (2019) showed that consumers consider AI-generated advertising copy to be less persuasive and authentic than that created by human copywriters. Our qualitative study also contributes to deepening the reasons why customers tend to reject using AI-generated images for commercial purposes. They perceive that companies using AI-images are less reliable and less professional, raising doubts about the authenticity of the service. Furthermore, such images are often seen as deceptive, leading to skepticism about the company's intentions and transparency. Thus, our findings reinforce the importance of service providers' human value in consumer decision making.

Additionally, the distinction between hedonic and utilitarian services has been widely studied in the marketing literature (Chitturi et al., 2008; Dhar and Wertenbroch, 2000). Our findings reveal that the negative influence of AI-generated images on the behavioral intentions toward the service is stronger for hedonic services than for utilitarian ones. In this regard, Processing Fluency Theory (Reber et al., 2004) provides a valuable framework for understanding why real images can foster a more fluid experience and thus a more positive affective response, especially in hedonic services that rely heavily on emotional evocation. According to this theory, when image processing is easier, consumers report greater liking and trust, which is decisive in services that seek to highlight hedonic attributes (Winkielman et al., 2003). Our research confirms and extends these findings by showing that the negative perception of AI-generated images is more pronounced in hedonic services. Consumers seek a greater emotional connection and authenticity in these types of services (Belanche et al., 2024b; Huang and Rust, 2018), aspects that AI-generated images may not always convey effectively. The qualitative study reveals that customers require a clear visualization of the offered experience. They find this task to be easier when real images are displayed. Actual photos provide a tangible representation of what to expect, offering a more accurate idea of the service. Consumers also value empathizing with the company through real images, as these provide a sense of authenticity and transparency that AI-generated images often lack. This emotional connection is especially crucial for hedonic services, where the experience and enjoyment play a vital role in the decision-making process.

The literature on involvement (Petty et al., 1983; Zaichkowsky, 1985) indicates that consumers with high-involvement process information, which also includes the type of images used, in a more detailed and critical way. Our study provides evidence in favor of this effect in the AI domain, confirming that the negative influence of AI-generated images on behavioral intentions is more pronounced in high-involvement services than in low-involvement services. When involvement is high, consumers pay more attention to possible signs of manipulation or lack of realism (as is the case with certain AI-generated images), which hinders processing fluency (Reber et al., 2004). Thus, consumers with high-involvement question the authenticity of these images and distrust services marketed with these images, which reduces their intention to use and recommend the service. However, in low-involvement scenarios, where consumers do not spend as much effort evaluating information, the difference in perception between AI-generated and real images is less relevant. The results of the qualitative study further explain these findings, as consumers would distrust a service provider if they employ AI-generated images, since they are afraid of being manipulated or deceived by this content. The findings are also consistent with the limited literature in this area. A study by Kaplan and Haenlein (2010) on the influence of social media on brands found that, in high-involvement environments, consumers are more critical of the authenticity of advertising messages on social networks. This reinforces the idea that consumer involvement plays a crucial role in how customers evaluate advanced technology such as artificial intelligence.

Finally, the post-hoc analysis reveals a triple interaction effect. This extraordinary finding is particularly relevant and increases the value and contribution of our research. In particular, this result indicates that focusing solely on utilitarian services is not a sufficient reason to employ AI-generated images, as they still elicit negative reactions when consumer involvement is high. Likewise, AI-generated images should also be avoided when promoting low-involvement services that focus on hedonic value. In turn, our findings suggest that real images are generally most effective and that using AI-generated images for commercial purposes would only be advisable for low-involvement, utilitarian services, as we further explain in our managerial implications.

6.2. Managerial implications

With the evolution of AI in advertising, it is crucial that companies carefully analyze how and when to use AI-generated images in their campaigns. In general, companies should avoid using AI-generated images for commercial purposes to avoid potential controversy and damage to brand reputation. Using AI images leads customers to infer that the service provider may lack authenticity and professionalism, raising doubts about the accuracy of the representation and the company's intentions. Real images, on the other hand, are perceived as more trustworthy and aligned with customer expectations, helping to build their confidence in the service. Hospitality companies should consider the strategic advantages of AI, while remaining aware of potential pitfalls such as the risk of AI generating misinformation and the need for human oversight (Sigala et al., 2024). Given the particular features of this sector (Kim et al., 2016), customers are looking for authenticity, trust, and an accurate representation of the experiences they will have, so real images remain critical to convey credibility, especially in hotels, restaurants, and tourist destinations (An & Ozturk, 2022; Seo et al., 2025). The use of AI-generated imagery in this context could be perceived as misleading, potentially negatively affecting the perception of transparency and trust in the brand. In this way, the adoption of AI-generated images should be limited to specific cases or purposes.

In particular, the results of our research indicate that AI-generated images affect consumer perceptions differentially depending on the type of service. On one hand, our findings suggest that for services that seek to provide pleasure and emotional (hedonic) satisfaction, such as those related to leisure travel, fashion or entertainment, it is crucial to use real images. These results suggest that consumers highly value a genuine and credible emotional connection coming from real pictures taken by humans. By including human elements and personal narratives in campaigns, it could be strengthened the emotional connection, leading to an increase in the effectiveness of advertising (Dessart, 2018; Escalas, 2004). Therefore, companies should invest in photo shoots and in telling real stories that resonate with their audience and avoid the artificiality that comes with the use of AI-generated images. In hospitality, where the hedonic experience is central to the value proposition, our research findings suggest that companies should avoid using AI-generated images instead of real images. In this sense, our research suggest that hospitality companies should show real images; for instance, the presence of real people in photos displayed by hotels (Back et al., 2020), or diffusing guest-generated photos that reinforce the perceived credibility of the service, improve the value received and increase the intention to book (An & Ozturk, 2022). On the other hand, for utilitarian services where functionality and efficiency are the main considerations (e.g., when a hospitality service is just used for practical purposes), AI-generated images can be an effective and economical tool, especially for low-involvement services. The perception of authenticity is less crucial in these cases, and consumers value clear and straightforward information more. In low-involvement utilitarian hospitality services (e.g., quick-service restaurants), consumers process information with less caution, driven by a convenience goal, making AI-generated images more acceptable as they are effective in showing the service functionality. This is why companies can use generative AI to create visuals that highlight the practical features and benefits of their services, optimizing costs and production times.

The level of consumer involvement is another key factor that should be taken into account in marketing strategies. Real images can strengthen the perception of transparency and credibility, which is particularly requested by highly involved consumers in their decision-making. However, for low-involvement products and services, where consumers do not spend much time evaluating, AI-generated images can be sufficiently effective, especially if they are utilitarian products and services. These images can be visually appealing and communicate efficiently, quickly capturing the consumer's attention. In the hospitality industry, high-involvement services (e.g., choosing a resort for a honeymoon), involve high risks and intensive information search, so real images should be employed to reduce uncertainty. For instance, when considering a venue for an important social event, it would be helpful to observe images from a real event that has taken place in the same place. This way, credible visual evidence of the offerings will be displayed. In contrast, for low-involvement services, such as late check-out, which require less information processing, AI-generated images can be suitable for use. In these cases, consumers require quick, straightforward information rather than authentic content, turning AI-generated images into an efficient solution.

Thus, companies should carefully evaluate the trade-offs between cost efficiency and the potential customers' reactions when deciding whether to use AI-generated or real images in their marketing efforts. In addition, beyond the initial customer rejection of AI-generated images, companies should not forgo the potential advantages of AI. In the current highly evolving marketplace, companies should explore new AI-related creative frontiers to experiment with innovative styles and formats that would be difficult or costly to produce manually (Hartmann et al., 2025). By reducing costs and production times, generative AI would enable companies to be more agile and efficient in their marketing operations, allowing for rapid responses to market trends. For instance, generative AI can provide value in creative aspects, such as illustrating concepts not yet built (e.g., future resort projects), to favor communication with customers (Campbell et al., 2021).

Nevertheless, the use of generative AI in marketing raises ethical concerns that companies should manage carefully. Its ability to produce hyper-realistic images implies risks of manipulation and misinformation, particularly when representations do not match the actual characteristics of the promoted products or services (Floridi & Chiriatti, 2020). This challenges the principle of truthfulness in advertising, potentially misleading consumers and undermining transparency (Spurgin, 2003). The ease of modifying such images in real time further complicates traceability and increases the risk of emotional exploitation (O`Neil, 2016). To address these concerns, companies should clearly disclose when AI is used, which can reduce skepticism and foster trust (Arango et al., 2023; Sundar, 2020). Regulatory standards requiring transparency, such as indicating when an image is AI-generated, are essential to protect consumers and ensure responsible communication (Floridi & Cowls, 2021). These issues are especially relevant in the hospitality industry, where decisions are often made in advance and heavily rely on visual cues (Kim et al., 2016). In this context, consumers may over-idealize services displayed through AI-generated images, which may lead to expectation gaps and dissatisfaction (Oliver, 1980), ultimately harming brand perception. Consequently, the use of real visual materials is essential for hospitality companies, which should avoid the unethical use of AI to present inauthentic service images that do not align with reality.

6.3. Limitations and future research

The research limitations are detailed next, opening new directions for future research. First, although the experimental scenarios were carefully constructed to simulate realistic consumption decisions, they may not fully reflect the complexity of real-world contexts. This design prioritizes internal validity but may limit the external validity of the first study (Viglia & Dolnicar, 2020). Although the follow-up qualitative study corroborates the experimental findings, future research could employ field experiments or longitudinal designs to examine the effects of AI-generated images in more natural and diverse settings, especially given the rapid evolution of this technology. Future research could also examine a broader variety of AI-generated formats, such as text or video, across different service categories. Investigating the reactions of various audience segments, such as early adopters or tech-savvy consumers, could further enrich our understanding.

A second limitation is related to our analytical method. While our experimental design was suitable for testing causal effects, future studies could employ Structural Equation Modeling (SEM) to investigate the underlying mechanisms of consumer responses, including potential mediators or indirect effects. Our qualitative study partially solves this weakness. It relied on online open-ended surveys, which provide rich, nuanced data from geographically diverse participants and allow for more reflective responses; however, they lack the interactive nature of in-depth interviews, including the opportunity for real-time clarification (Braun et al., 2021). Future research could use semi-structured or face-to-face interviews to facilitate a deeper exploration of consumer thoughts and emotions through follow-up questions and adaptive probing.

The study was conducted in a specific cultural environment, which may have influenced the results, as perceptions of authenticity or the need to justify hedonic consumption differ across cultures. For instance, Okada (2005) suggests that the guilt associated with hedonic choices is more salient in cultures emphasizing frugality and hard work, such as the U.S., but may be less relevant in other cultures. Future studies should replicate this research across diverse cultural contexts to assess cross-cultural variation in consumer responses to AI-generated content, thereby increasing the generalizability of the findings. Moreover, while this study focuses on the hospitality sector, the implications of AI-generated content may not fully translate to other industries. Although the benefits and challenges of generative AI are broadly applicable, sector-specific factors (e.g., the nature of the service, the degree of pre-purchase visualization) can influence the results (Kim et al., 2024; Ng et al., 2024). Therefore, future research should investigate how these dynamics impact other sectors.

Finally, our research assumes that participants can consistently distinguish between real and AI-generated images, as checked through a control question in our firs study. However, recent literature suggests that when this information is not disclosed, consumers may not reliably distinguish between AI-generated and real images (Pocol et al., 2024). As AI continues to produce increasingly realistic images, future studies should investigate whether the observed effects persist when the AI nature of the content is either undisclosed or ambiguous. In this regard, given the growing ethical concerns associated with the use of generative AI in advertising (Campbell et al., 2022), future work should explore consumer perceptions of manipulative or deceptive uses of AI content and how companies can manage such practices responsibly.

CRediT authorship contribution statement

Daniel Belanche: Writing – original draft, Methodology, Funding acquisition, Data curation, Conceptualization. **Sergio Ibáñez-Sánchez:** Writing – review & editing, Methodology, Investigation, Formal analysis, Conceptualization. **Pau Jordán:** Software, Investigation, Writing – review & editing, Visualization. **Sergio Matas:** Writing – original draft, Methodology, Formal analysis, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT4 to check language grammar and improve readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix 1. – Manipulations

Real (left) and AI-generated (right) images of the hedonic highly involvement scenarios

	Utilitarian	Hedonic
High-involvement	Imagine that your company is holding a large business event that will be attended by some of the company's strategic partners. Imagine that your company has entrusted you with the important task of finding a caterer for the meal. The brief is that it should be efficient and practical so that they rate it positively, there are no problems, and they can get on with their work. The aim is to have something to eat, not to enjoy, but it is very important that everything runs smoothly.	Imagine you have a large group of friends and this time you have been given the important task of choosing the hotel for the week's holiday you are going to enjoy together this summer. Your friends have told you that they want to enjoy the hotel, its facilities, leisure activities in the area, food and drink and they expect to have a great time. Enjoyment is the aim and is very important, but it doesn't need to be practical as you are on holiday.
Low-involvement	Imagine that, although it was not planned, you have to stay for lunch at work with colleagues who ask you to help them find options on where to go for lunch because they don't care. Lunch is not important today. Your idea is to make it quick, efficient and practical so that there is no problem and you can get on with your work. The aim is to eat something, not to enjoy, it is an inconsequential decision.	Imagine you are enjoying a day out with your friends at an amusement park, and you have half an hour of downtime, so you decide to find a café to have an ice cream. Although it's a minor decision, you want to enjoy the experience, be at ease in the place, savor the ice cream, cool off, and hang out. The goal is to enjoy, but it doesn't need to be practical since you are on holiday, it is an irrelevant decision.

Appendix 2. - Scales of measurement

Service type, hedonic vs. utilitarian. Scale adapted from Hassan & Casaló (2016).
The service I needed was …
… 1 'practical' 7 'experiential'.
… 1 'useful' 7 'pleasurable'.
… 1 'utilitarian' 7 'hedonic'.
Involvement. Scale adapted from Zaichkowsky (1985).
The decision I have been asked to make ….
… 1 'is unimportant to me'/ 7 'is very important to me'.
… 1 'is irrelevant to me'/ 7 'is very relevant to me'.
… 1 'it means nothing to me/ 7 'it means a lot to me.
Behavioral intention. Scale adapted from Bhattacherjee (2000).
I would use the service shown in the image.
I would very likely book the service shown in the image.
I would book the service shown in the image.
Positive WOM. Scale adapted from Harrison-Walker (2001).
If someone asks me about the service shown in the image, I would give them a positive opinion.
If I had the opportunity, I would highlight the advantages of the service shown in the image.
From the image shown, I would recommend this service.

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