







Evaluating tourism destination images: Integrating survey, neural responses and artificial intelligence

Kathrin Jaszus^a , Anett Erdmann^{b,c,1} , Jose M. Ramos-Henríquez^{d,e,*} ,
Jose M. Mas-Iglesias^{b,c,2} 

^a Business School, Trier University of Applied Sciences, Trier, Germany

^b Academic Marketing Department, ESIC University, Madrid, Spain

^c ESIC Business & Marketing School, Madrid, Spain

^d Department of Business Administration and Economic History, Business and Tourism Faculty, University of La Laguna, S/C Tenerife, Spain

^e IUDE, University of La Laguna, S/C Tenerife, Spain

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ABSTRACT

This study introduces a triple-method approach to evaluate tourism destination attractiveness by integrating consumer surveys, neurophysiological measurements, and large language models (LLMs). Drawing on dual-process theory as a conceptual and interpretive framework, we examine how different measurement methods, individually and in combination, can help explain tourists' preferences for destination images. The study involved 96 participants from two countries who were shown in an experiment ten images representing various tourism types while collecting self-reported data, neurophysiological measurements, and LLM-based image assessments. To analyze image rankings and relative preferences, we adopted a multi-stage analytical approach. Our findings suggest that each measurement method captures distinct aspects of tourist decision-making: Survey measurements primarily correlate with fast-affective responses. Neurophysiological data reveal affective and cognitive responses not detected in self-reports. LLMs offer complementary evaluations. However, the incremental explanatory value of LLM-based assessment varies by image-type. Combined measurements also differ in effectiveness across tourism types, underscoring the need for tailored evaluation approaches.

1. Introduction

The image of a tourist destination plays a crucial role in travelers' decision-making processes and behavioral intentions. Destination image significantly influences tourists' intentions to visit, revisit, and recommend a location (Afshardoost & Eshaghi, 2020). Destination management organizations (DMOs) invest significant resources in selecting and promoting images that capture the attention of potential visitors and generate positive emotional responses. While traditional self-report questionnaires have long been the primary tool for measuring emotional responses and value perceptions (Zentner & Eerola, 2010), these methods are susceptible to cognitive biases and social desirability effects (Li et al., 2023). This measurement challenge has prompted researchers to explore alternative approaches, including

neurophysiological tools and artificial intelligence (AI) applications, to better understand the complex cognitive and affective components that shape perceptions of destination (Bastiaansen et al., 2022; Sigala et al., 2024).

Recent advancements in neuroscience have enabled the use of tools like electroencephalography (EEG) to provide psychophysiological indicators that reflect and index affective responses and cognitive load (Bastiaansen et al., 2024). Simultaneously, the emergence of large language models has opened new possibilities for analyzing consumer perceptions of visual stimuli (Sigala et al., 2024). Initial studies suggest that combining surveys and neurophysiological data can enhance the prediction of experimental behavior (Albuquerque et al., 2025). Despite these advancements, research integrating multiple measurement methods remains scarce in tourism. Three research gaps remain in

* Corresponding author. Facultad de Economía, Empresa y Turismo, Universidad de La Laguna, Campus de Guajara, Tenerife, 38071, La Laguna, Spain.

E-mail addresses: jaszus@hochschule-trier.de (K. Jaszus), aerdmann@comillas.edu (A. Erdmann), jramosh@ull.edu.es (J.M. Ramos-Henríquez), josemas@ucm.es (J.M. Mas-Iglesias).

¹ Present address: Department of Marketing. Universidad Pontificia Comillas. Madrid. Spain.

² Present address: Department of Marketing. Universidad Complutense de Madrid. Madrid. Spain.

tourism destination analysis. First, there is a limited understanding of how different data collection methods (self-report, neurophysiological, and AI-based) compare in capturing tourists' responses to destination imagery (Bastiaansen et al., 2022; He et al., 2021; Li et al., 2023). Second, the evidence regarding which measurement approach, or combination of approaches, most accurately predicts actual destination preferences remains unclear (Kanazawa et al., 2021; J. S. Lee & Park, 2023). Third, while integrated approaches show promise, their combined predictive power compared to single-method approaches has not been evaluated in tourism settings.

To address these gaps, we propose a novel trimodal methodological approach that integrates traditional self-reported surveys, neurophysiological measures (EEG), and AI-based assessments of destination imagery. This integrated approach is guided by the research question: To what extent do different data collection methods (self-report, neurophysiological, and AI-based) capture tourists' destination image preferences, and what factors explain these variations?

We use dual-process theory (Evans & Stanovich, 2013) as a conceptual lens, which has been widely adopted in behavioral economics and in the context of tourism decision-making to explain human reasoning (Kim et al., 2025; Stylos, 2022). We argue that tourists' multifaceted cognitive-affective value perceptions are processed through different systems: System 1 (intuitive) and System 2 (reflective), which AI-based assessments can complement as a third, artificial processing system. While tourism literature has explored the conceptualization of multidimensional value, research has typically been limited to either functional specification of survey data (Babin & Kim, 2001) or specific types of neurophysiological data (Bastiaansen et al., 2022).

The study employs an experimental, bi-national laboratory design combining image preference rankings with ordinal preference evaluations and a triple-method data approach to capture cognitive and affective responses. Differences between samples are interpreted descriptively, with the country indicator reflecting contextual, temporal, and market-specific factors rather than cultural effects. The measurement approach has three data-type components: (1) self-reported preferences, values, and emotions from surveys; (2) biometric measurements, such as EEG data; and (3) LLM-based image analysis.

A multi-stage analytical approach is adopted. First, we examine the relative preference strength of the images (Plackett–Luce model). Second, we estimate a rank-ordered logit model incorporating covariates from survey-based, neurophysiological, and LLM data to explore which variables best explain the observed preferences. Third, ordered logit models are estimated at the image level for different combinations of the distinct data types. This allows for evaluating how individual characteristics are associated with a higher or lower assessment of a particular tourism type. That is, we examine the explanatory power of each data type individually and in combination, considering both the entire preference set as well as individual images.

This study contributes to destination marketing research in two ways. Methodologically, it introduces and evaluates a triple-method approach that responds to recent calls for multi-method designs in tourism (Albuquerque et al., 2025; Bastiaansen et al., 2025) and practical applications of generative AI in consumer evaluation (Hsu et al., 2024). This integration addresses the fragmented literature, which has tended to examine each approach in isolation, and highlights the advantages and limitations of each method in explaining destination image preferences. Practically, it provides guidance to DMOs on selecting appropriate assessment tools for designing and evaluating visual marketing materials.

2. Literature and hypotheses development

2.1. Destination image and visual communication

The destination image is a key element in tourism research, including what tourists believe, think, and feel about a place (Cerić et al., 2024).

The image tourists have of a particular destination significantly influences their decision-making process, as potential visitors form mental representations of destinations through various information sources and interactions (Afshardoost & Eshaghi, 2020; Liu et al., 2024).

In the literature, perceived destination image is a multidimensional concept that encompasses cognitive components related to knowledge and beliefs about destination attributes, as well as affective components reflecting emotional responses to the destination. Some authors also include conative elements that influence behavioral intentions (Wang et al., 2024). However, conative elements are not considered explicitly in this study. Examining destination image from the perspectives of key source markets has become critical for strategic management of destination attractiveness, as perceptions of destination image attributes vary significantly across visitor markets (J. S. Lee & Park, 2023).

The visual content analysis of tourist photographs reveals that destination images are constructed through multiple perspectives, including scenic elements, visual aesthetics, and emotional experiences, creating a comprehensive understanding of how destinations are perceived and evaluated by visitors (Wang et al., 2024).

Visual communication through carefully selected photographs plays an important role in shaping a destination's image and facilitating successful tourism marketing strategies (Cerić et al., 2024). Images possess unique communicative power that transcends linguistic barriers, enabling destinations to convey complex experiential promises and emotional connections more effectively than textual descriptions alone. Tourists' image formations are significantly influenced by the strategic selection and presentation of photographs of tourist destinations, especially when enhanced by social media (Liu et al., 2024). Contemporary research using computer vision and deep learning shows that photos are powerful tools for understanding tourists and depicting destination images (Wang et al., 2024). Social media has increased the importance of visual storytelling in destination marketing. This makes it essential to carefully analyze and select photographic content to maintain a competitive advantage and effectively communicate the brand identity to target audiences across diverse markets.

2.2. Consumer choice in tourism and dual process theory

Multiple factors influence consumer preferences for different types of tourism and destination activities. Behavioral decision research has long tried to understand why people make certain choices and why they make “mistakes” in their decisions relative to economic models of rational understanding of consumer preferences. It suggests that individuals often rely on mental shortcuts arising from differential cognitive processing – relying on heuristic judgement (rules of thumb) which are known to be a biased approach but accepted to frame the idea of intuition and reason - and this perspective adopted the distinction between an intuitive system and reflective judgments (Kahneman & Egan, 2011; Tversky & Kahneman, 1973), which brought on the way the dual-process theory framework. As a cognitive-psychological framework for decision-making, the dual-process perspective explains the interplay of analytical and intuitive decisions in customer reasoning and decision-making (Evans & Stanovich, 2013). While the authors note that the dual process theory lacks a universally agreed-upon definition, it offers behavioral economists a way to explain the dynamics of choice beyond the “anomalies” of utility maximization and has thus become a widely adopted explanatory framework in behavioral economics (Grayot, 2020). According to Evans and Stanovich (2013), consumer thinking can be categorized into two systems: System 1, which is fast, intuitive, and automatic, and System 2, which is slow, careful, and deliberate, requiring conscious effort and more time.

Dualistic models of reasoning provide frameworks that facilitate the interpretation of observed outcomes and serve as useful simplifications that render reasoning more structured and interpretable. Despite the absence of a unified theory, the heuristic logic of dual-process reasoning has become the standard view, what Mugg (2016) calls the “Standard

Menu”, establishing itself as the dominant conceptual baseline for research on reasoning and decision-making.

However, no model framework is perfect and the dual-process framework does not capture the full complexity of the human mind, with the main criticisms being as follows: (1) the systems are not truly discrete, and there is little evidence linking them to a fixed neural architecture, instead, overlapping and cross-cutting processes are observed, (2) there is limited evidence for inter-system interactions, whether sequential or parallel-competitive (and some have even proposed a third executive mechanism), and (3) empirical support for dual process theory remains largely confined to controlled laboratory settings (Grayot, 2020). Given this synthesis of the main criticisms concerning reliability and accuracy, the authors argue that the dual process theory explains a mechanism but is not a mechanistic theory of mental functions. Rather, it represents a functionalist approach that helps capture and describe the underlying mental processes, “opening the black box” where traditional economic constructs fall short in understanding preference formation.

The relative importance of the underlying processes is particularly relevant for marketing purposes. Dhar and Gorlin (2013) explore the conditions under which more intuitive reasoning or more deliberate processing is likely to drive heuristic judgment, thereby influencing preference construction and its variation across contexts.

In the context of tourism decision-making, Stylos (2022) explains how tourists' intuitive and deliberative thinking processes work together. Lindberg and Stemmer (2022) find that the use of the deliberative system depends on respondents' habitual decision styles (intuitive or rational) and on researcher interventions. In the same vein, Kim et al. (2025) build on the dual process theory framework to explain how tourists process information cues on online travel agency websites, such as the priming effects of social media posts. Thus, the dual process theory has also become, in tourism, a blueprint for understanding the architecture of how people process provided information.

Consequently, depending on the evaluation context, these two types of processing can complement or compete. Consumer decisions, which influence consumer satisfaction, often involve both System 1 and System 2 decisions, and these decisions are based on perceived value. Evaluations are usually studied using value ratings and hierarchies of variables (e.g., Zeithaml, 1988). However, the concept of perceived value is complex and has a very interdisciplinary nature, which is why no single measurement approach can fully capture it (Boksberger & Melsen, 2011). In tourism literature, a multidimensional conceptualization of perceived value is standard (Babin & Kim, 2001), considering that there is an interplay between cognitive and emotional value processes that aligns with the dual-process theory of consumer decision-making.

2.3. Methods for measuring response in tourism

Pictures should stimulate cognitive and emotional brain activity to promote a destination. Traditionally, self-reported measures have been used to assess respondents' emotional states (Hosany et al., 2020). These measures often involve questionnaires, where respondents rate their attitudes toward a particular stimulus, such as a photo of a specific type of tourism. In practical applications, Mehrabian and Russell's (1974) Emotional State Model has been widely applied. While this method is cost-effective and easy to implement, it carries the risk of potential emotional bias due to the delay between stimulus exposure and data collection (Volo, 2016).

One method of avoiding biased data is to use a neurophysiological tool, such as an EEG, which is widely regarded as capable of detecting cognitive and emotional brain activity (Li et al., 2022). The tool is non-invasive, relatively inexpensive, and measures four factors: attention, emotional valence, memorization, and working memory. In tourism research, EEG has become a valuable tool to compare emotional and cognitive reactions while contemplating tourism-related stimuli. Early studies showed that emotional responses to images can be

captured more effectively using an EEG-helmet than only self-report methods (e.g., Bastiaansen et al., 2018; Tosun et al., 2016). L. Hsu and Chen (2020) explored the influence of unconscious emotional cues in hotel marketing videos on consumer preferences, while Fronda et al. (2021) used an EEG-based approach to show that emotional reactions in sustainable tourism are stronger to “green” messages than to neutral ones. Actual studies have transferred these findings to more complex contexts, like joint decision-making or environmental perception. Bastiaansen et al. (2025) analyzed emotional responses to overcrowding in tourism settings.

Recent research in visual content analysis provides DMOs with alternatives to traditional subjective evaluation methods. Wang et al. (2020) developed an AI framework to improve the classification of tourism images. He et al. (2021) used machine learning to extract from user-generated image pairs of adjective + noun (e.g., beautiful + beach) to capture the cognitive and affective elements of these tourism photos and construct semantic networks that represent the collective perception of a destination from tourist-generated photos, guiding content selection strategies by destination management organizations. While the authors focus on user-generated image content, tourists' decision-making responses in destination selection remain a black box. To better understand the human decision-making mechanism, additional human-based responses are needed. However, to the best of our knowledge, very few studies have examined LLM-based image assessments in evaluating human responses, and none have done so within a trimodal framework combining surveys and neurophysiological measures. Existing work has focused only on synthetic assessments more broadly. Arora et al. (2025) underscore the complementary nature of human evaluations and LLM-based analyses, highlighting the added value of integrating both through a hybrid approach to customer understanding. Advanced AI systems, including OpenAI's GPT-4o or Claude 3.5 Sonnet, further increase the potential of touristic image-related data. These integrated LLMs can create images from text, analyze visual content, and derive insights from image assessment. However, the application of tourism-related photo analysis with LLMs remains very limited. Prior tourism studies mainly focus on pictures generated by advanced AI systems (e.g., Zhu et al., 2024). Only Viglia et al. (2024) conducted a comparative photo analysis using the Gemini-1.5 Pro-128k model, indicating a research gap in image analysis in tourism with advanced AI systems.

Humans increasingly rely on LLMs for decision-making, which shapes their preferences and choices beyond traditional human processes (which can be framed within dual-process theory). Input from AI solutions becomes critical for determining preferences and is increasingly considered emotionally sensitive (Ahmad & Mir, 2025). Accordingly, LLM-based assessment can be understood as a third system, representing an important pillar in consumers' decision-making processes and, consequently, in decision-process analysis. Just as humans expect support from these systems, we expect them to provide additional insights beyond those obtained through self-report in preference formation. In line with Arora et al. (2025), generating efficiency gains using hybrid assessment, but from the perspective of rank-ordered preference assessment of image stimuli. In this context, it is important to note that the assessment process in any AI system depends fundamentally on the system's architecture, particularly the cognitive structure of the model and its training data (Wiesinger et al., 2025). Nevertheless, cognition in the context of synthetic analysis should not be equated with human cognition but rather understood as a machine-based system that can be activated to support decision-making. Using artificial intelligence in behavioral analysis has the potential to equip DMOs with data-driven methodologies for understanding, measuring, and optimizing human responses to visual destination marketing content. However, any extrapolation of human behavioral theories, such as dual-process theory and the differentiation of cognitive and affective elements, to synthetic responses requires careful empirical validation.

2.4. Integrating the data into the theoretical approach

Dual-process theory provides a foundation for synthesizing data and understanding rational and intuitive behavior (Kahneman & Egan, 2011). Considering survey data, different dimensions of tourists' perceptions can be analyzed and mapped to observed rank-ordered value preferences. While completing the survey, respondents are expected to process most information quickly and intuitively, primarily using System 1. However, when asked to rank the pictures according to their preferences, on a scale from 1 to 10, participants need to think carefully and deliberately about what belongs to System 2 rather than System 1 (Evans & Stanovich, 2013).

Information processing considering neurophysiological data can also be divided into two systems: a fast-affective system, focusing on valence and engagement (Bastiaansen et al., 2022), and a more effortful cognitive one, including working memory and memorization (Michael et al., 2019). LLM-generated assessments are quick and probabilistic outcomes. Cognitive biases and suboptimal decisions may follow if people rely too much on AI suggestions (Bućinca et al., 2021). Each method for measuring consumer preferences for destination images is strong in some areas but less so in others. Hence, we set up the following hypotheses.

Hypothesis 1. Different data methods yield different outcomes, capturing complementary aspects of tourist destination image evaluation.

Hypothesis 2. The relative importance of each measurement approach and the data variability differ across tourism type images.

Hypothesis 3. Integrating self-reported, neurophysiological, and AI-based measures improves the predictive power of destination image preferences compared to a single method.

Fig. 1 illustrates the triple measurement approach to tourism preferences.

3. Methods

3.1. Research rationale

Two experiments were conducted. First, the neurophysiological experiment was performed (Study 1a). Then, participants physically ranked tourism-type images (Study 1b). In the next step, they completed an online survey (Study 1c) (Supplement A). Finally, LLMs rated the images, simulating each participant (Study 2).

3.2. Participants

For the first experiment, we recruited 56 German participants through professional contacts and snowball sampling. Six participants were excluded due to incomplete survey responses, resulting in a final sample of 50. The sample size was determined based on the exploratory nature of the study and practical constraints related to the neurophysiological measures. For the second phase, we similarly recruited 50 Spanish participants using the same approach, with 46 completing the image ranking task. The gender distribution was balanced across both samples. Spanish participants' ages ranged from 22 to 61 years (M = 41.4), while German participants' ages ranged from 21 to 66 years (M = 35.0). Data collection took place in Germany from June to July 2022 and in Spain from March to June 2023. As data collection took place in different periods, comparisons across samples may reflect contextual timing effects that cannot be fully separated from cross-market differences. Regarding familiarity with the study location, 44% of German respondents and 19.6% of Spanish participants reported never having visited the Balearic Islands (see Supplement B). All participants self-reported normal or corrected-to-normal vision and hearing.

3.3. Locations

The German data collection was realized at a university in Rhineland-Palatinate, and the Spanish data collection took place at a university in the Madrid region. Both institutions provide suitable environments for neurophysiological measurements and the administration of questionnaires. The studies were carried out by the same team using the same transportable laboratory at both locations.

3.4. Experimental procedure

The Balearic Islands were chosen as the destination for our experiment because the two participant samples represent the principal European source market for the destination. Together, these markets accounted for more than 45% of total visitors in 2023 (IBESTAT, 2025). Besides their quantitative importance, prior research and market reports indicate heterogeneity in destination image perceptions and travel-related behavior across the two source markets (e.g., FUR /ForschungsgemeinschaftUrlaubundReisene.V, 2024a, FUR/Kompetenzzentrum Tourismus, 2024b; J. S. Lee & Park, 2023; Ministerio de Industria y; Turespaña, 2025; Turismo, 2023; Wang et al., 2024). These documented differences motivate a comparative, cross-market examination of image preferences and decision-making processes.

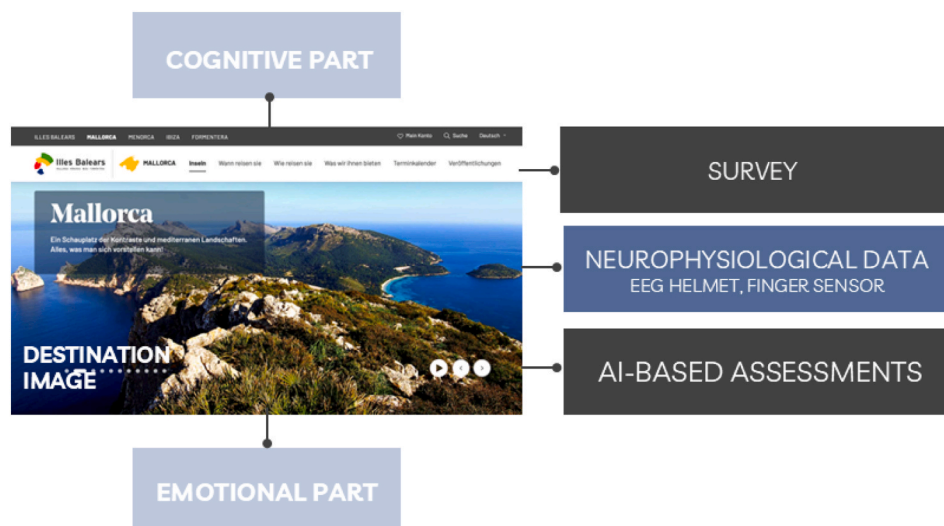


Fig. 1. Integrated approach to measuring cognitive and emotional aspects of destination image preferences.

For the image ranking analysis, we extracted photographs from the official website of the Balearic Islands' DMO: illesbalears.travel. Ten photographs were selected based on three criteria: (1) temporal consistency (all images were published on the official website in March 2022); (2) representational diversity (the selected photographs captured various types of tourism available throughout the archipelago); and (3) experimental feasibility (the number of images was limited to ensure that neurophysiological experiments could be completed within an hour). To minimize selection bias, two authors independently conducted the selection process, following these predefined criteria.

The experiment took approximately 1 h per participant. Initially, participants were randomly selected and provided with written instructions. They were required to sign a consent form for data processing and briefed on the experiment's procedure and the basic functionality of the equipment. The neurophysiological equipment included two wireless mobile devices from BitBrain: (1) EEG "Diadem" - a 12-channel dry EEG sensor for monitoring brain activity; (2) The "Ring" - a finger sensor for measuring heart rate.

The BitBrain Diadem headset was placed at specific head positions to measure brain activity according to the international 10-10 standard (Koessler et al., 2009): FP1, FP2, AF7, AF8, F3, F4, P3, P4, PO7, PO8, O1, O2. FP describes the pre-frontal, F the frontal, C the central, T the temporal, P the parietal, and O the occipital brain areas. Odd numbers indicate that the electrodes are placed on the left side of the scalp, even numbers refer to those on the right side (Ortiz, 2020). Furthermore, the "Diadem" contains a ground (GND) and a reference (REF) sensor. The ground electrode serves as a common reference point for EEG signals, helps to reduce the electrical noise, and improves signal quality. The reference sensor is placed at the left ear loop. It provides a baseline voltage against which the EEG signals from GND are compared (Bitbrain, 2024b).

The device outputs composite metrics of attention, emotional valence, memorization, and working memory, which are derived from frequency band ratios (alpha, beta, and theta) and locally weighted electrode measurements (Bitbrain, 2024a). The neurophysiological measures of emotional valence and engagement are interpreted as fast-affective correlates of immediate response, which is consistent with the intuitive nature of System 1 thinking (Bastiaansen et al., 2020; Li et al., 2022). Similarly, working memory and memorization are employed as more effortful cognitive correlates aligned with the deliberative processing of System 2 (Michael et al., 2019). Even if the vendor-defined values were utilized, prior research has shown that similar metrics are in line with approved psychophysiological indicators of emotional and cognitive processing (e.g., Bastiaansen et al., 2022; Li et al., 2022). According to the dual-process theory, attention and emotional valence as part of emotional reactions are categorized as System 1. In contrast, memorization and working memory belong to rational and controlled processes typical of System 2.

All neurophysiological indices were computed using Bitbrain's proprietary software development kit and SennsMetrics platform (Bitbrain, 2024a). It is important to clarify that these measures do not represent direct observations of internal cognitive mechanisms; instead, they reflect response patterns that align with dual-process theory as established in previous literature. The EEG outputs consist of approved psychophysiological indicators that are vendor-defined composite metrics derived from proprietary software, and are therefore treated as relative indicators of emotional and cognitive engagement rather than direct mechanistic measures of discrete dual-process systems or localized neural activity (Bastiaansen et al., 2022; Li et al., 2022).

Signal preprocessing steps, including filtering, baseline normalization, and basic artifact handling, were conducted automatically by the software, while researchers retained control over the experimental design, including stimulus selection, presentation timing, calibration procedures, and the selection of output metrics used for analysis.

EEG-based results are interpreted exploratively and indicate relative affective and cognitive engagement rather than definitive evidence

based on directly interpretable neural features. The neurophysiological measures, therefore, complement survey-based and behavioral findings by providing convergent, triangulated insights from different methods.

After adjusting the sensors, participants viewed images displayed on a laptop. SennsLab software was used to present the stimuli and to synthesize the data (Giakoni et al., 2022). These images included babies or puppies, poor neighborhoods, and cockroaches, aiming to assess emotional arousal. Following this familiarization phase, a 2-min "washout" period was introduced. During this time, participants focused on a white cross to reset their attention and enhance concentration. In the subsequent step, respondents were presented with the central stimuli: ten pictures representing different types of tourism³ that can be realized on the Balearic Islands (Fig. 2): (T1) gastronomic tourism, (T2) active holidays, (T3) cultural holidays, (T4) adventure holidays, (T5) relaxing holidays, (T6) family holidays, (T7) party tourism, (T8) nature tourism, (T9) health holidays, (T10) beach holidays.

Participants were also asked to rank printed and laminated images of the same tourism types based on their preferences, assigning values from 1 (lowest) to 10 (highest). They then entered this ranking into an online questionnaire after answering questions about age, gender, and previous visits. Finally, they completed the rest of the questionnaire, ranking the images based on the emotional impact generated and their perceived value. In the survey, emotions were measured using the Emotional State Model scale (Mehrabian & Russell, 1974), while the perceived value was assessed as an overall evaluation of costs and benefits (Kim et al., 2007).

3.5. Prompting

For the LLM-based assessment, we used two large language models, OpenAI's GPT-4o and Anthropic's Claude 3.5 Sonnet, to generate synthetic rankings of the tourism images. These were the most advanced models available at the time of the experiments (November 2024).

Each model was prompted with four text prompts, written in two languages (Spanish and German), and two versions of the persona evaluated the images. In the basic persona condition, only the country and city of origin were provided. In the extended persona condition, age, gender, and previous visitation status to the Balearic Islands were additionally included. A key consideration for reproducible LLM prompt executions is that the prompts were manually executed on the web form. Each prompt started a new chat on the browser, and the detailed prompt presented was pasted in.

In each prompt, all ten destination images used in the experiment were included. Because it was technically not possible to add all photographs simultaneously into the web browser window, the photographs were compiled into six composite-images and presented in random order to every web prompt window (each of the six composite-images included the ten photographs arranged visually in a different order). Prompts were written in the same language as the persona. The procedure was repeated for each valid human participant, yielding 192 ranking sets per LLM (96 participants × 2 persona configurations). All prompt versions are documented in Supplement C.

Each prompt followed the same basic structure. It (1) described the persona/role condition, (2) asked the model to rank the images in the same way as human participants, (3) specified the required output

³ The travel types are adapted from the *Reiseanalyse*, the largest and longest-running representative survey in Germany about travel behavior, motives, and holiday preferences (FUR, 2024a). For a better understanding, similar travel types can be differentiated as follows: active holidays include moderate physical activities like hiking, cycling, or skiing; adventure holidays describe experience-oriented and riskier activities such as trekking, climbing, or rafting; typical for beach holidays are stays at the seaside or lakeside focused on swimming and sunbathing; the main objective of relaxation/wellness holidays is to rest, regenerate, and enjoy wellness services (FUR, 2024a).

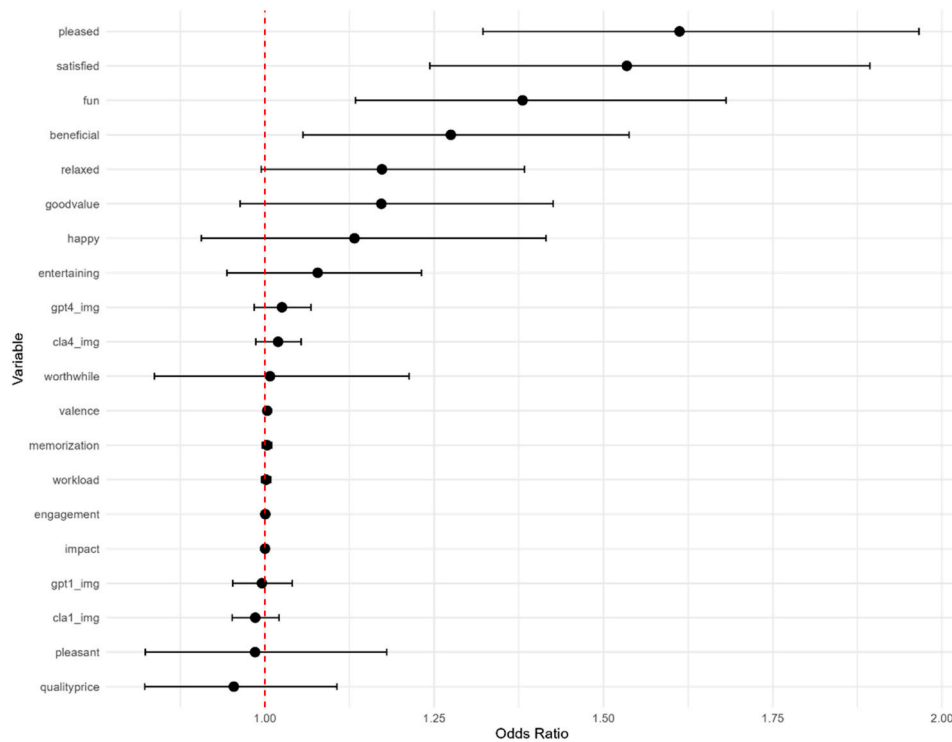


Fig. 2. Stimuli used showing ten different types of tourism from the official website of the Balearic Islands tourism board.

format, and (4) encouraged the model to consider detailed criteria and show authentic interest in the different types of tourism experiences when making its ranking. Several prompt versions were pre-tested in advance to ensure unique rankings and to reduce potential order effects.

To assess robustness, we tested the sensitivity of LLM rankings to both image order and prompt formulation. Image order effects were examined using alternative random orderings of the composite images, with one randomized ordering attached to each prompt. Prompt robustness was evaluated using a paraphrased version of the primary prompt, and a variant with more explicit ranking instructions in addition to the paraphrased version. All robustness analyses were conducted on the same subsample, and results are reported in Supplement M.

3.6. Data analysis

Understanding consumers' values is essential to understanding their purchasing choices (Luce, 1959). The literature distinguishes between ranking and rating methods for measuring preferences. While ranking alternatives provides detailed insights into relative preferences, it is cognitively demanding, time-consuming, and tends toward linear dependency (Alwin & Krosnick, 1985). In contrast, rating-based approaches, typically applied in survey research, often utilize Likert-type scales, save time, apply parametric statistical procedures, eliminate forced ranking, and do not require respondents to make explicit trade-offs between options (Marley, 1968). Munson and McIntyre (1979) find robust patterns across ranking and rating methods, while Ben-Akiva et al. (1992) point to greater detail and reliability of ranking data for modeling preferences.

In this study, tourism preferences are operationalized exclusively through rank-order data. The participants assign a unique rank to each tourism-type image. These rankings constitute the primary dependent variable, incorporating self-reported data, neurophysiological indicators, and LLM-based assessments as independent variables.

According to Luce's (1959) choice axioms, the probability of observing a specific ranking can be expressed as a function of latent utilities linked to each option (Luce, 1959; Marley, 1968). Ranking data

are rather a sequence of relative choice decisions than an independent ordinal evaluation. Therefore, model approaches that explicitly consider the sequential and comparative nature of ranked alternatives are needed. We have decided to use a three-step approach.

First, a Plackett–Luce model (Plackett, 1975) was estimated, which aggregates individual ranking decisions into an overall preference structure. The model interprets each ranking as a sequence of choices and estimates the probability with which the image is preferred relative to the others.

Second, building on this aggregated preference structure, a rank-ordered logit model (Beggs et al., 1981) is estimated to examine which image-related characteristics predict higher preference rankings. In our model, the dependent variable was the rank position of each image, while emotional responses and value-related assessments from surveys, neurophysiological measures, and LLM-based variables served as predictors. Thus, the relative explanatory contributions of each measurement approach within a unified discrete choice framework can be explained.

Third, for a detailed image-related analysis, we estimate six different ordered logit models for each of the ten photos. While the rank-ordered logit model describes the relative preferences across images, the logit models compare rankings yielded by different measurements. Model 1 is thereby solely calculated using survey data. Model 2 considers neurophysiological data alone. Model 3 refers solely to synthetic LLM data, while Model 4 combines survey and AI data. Model 5 links survey and neurophysiological data, and Model 6 considers a triple approach of survey, neurophysiological, and LLM data. An additional Model 0 was calculated based on contextual data. We analyze preferences for different types of tourism images and investigate whether there are systematic differences in consumer preferences. Through the stepwise modelling strategy, the explanatory contribution of each data source is visible. Throughout the paper, odds ratios from ordered logit models are reported. Percentage statements refer to proportional changes in odds rather than probabilities; changes in predicted probabilities depend on the baseline distribution across ranking categories.

4. Results

4.1. Preferences for the displayed image

To determine participants' image preferences, ranking data from 96 participants were analyzed using rank-ordered data models.

The results of the Plackett-Luce model (see Supplement D), estimated to identify the overall preferences across the images, show substantial differences in the relative evaluation of the images. This confirms that the preferences are not randomly distributed. Image 5 is significantly preferred (with a probability of being chosen first of 0.2009, $p = 0.007$), while Images 4 and 7 are significantly dispreferred (with worth parameters of 0.0563 and 0.0418, respectively, $p < 0.001$). The middle group (images 1, 3, 8, and 10) is statistically indistinguishable from itself, followed by a group slightly below average (images 2, 6, and 9). This tiered structure reflects a coherent preference ordering across tourism types.

The rank-ordered logit model includes covariates to determine which variables significantly predict the image rankings (see Fig. 3), showing that self-reported emotional variables—particularly pleased, satisfied, fun, and beneficial—are the strongest predictors of higher-ranked images. Among the neurophysiological measures, valence shows a small but significant effect, while LLM-based variables do not reach statistical significance in the aggregate ranking model.

To further examine whether these relationships differ across tourism-type images, the analysis proceeds with image-specific ordered logit models. The most significant predictors of image preference were survey-based emotional responses. Images associated with higher levels of *pleased* (OR = 1.59, $p < 0.001$), *satisfied* (OR = 1.54, $p < 0.001$), and *fun* (OR = 1.39, $p = 0.001$) were significantly more likely to be ranked higher. In relative terms, images rated higher on *pleased*, *satisfied*, and *fun* were chosen 59%, 54%, and 39% more often. Furthermore, the value-related item *beneficial* showed a significant positive effect (OR = 1.27, $p = 0.012$). Among the neurophysiological measures, valence was also a significant predictor of preference (OR = 1.003, $p < 0.001$). The emotional item *relaxed* was marginally significant (OR = 1.18, $p = 0.054$), while all remaining variables did not reach statistical significance.

Overall, emotional response variables dominate the prediction of image preferences. Images rated as pleased are chosen 61% more often, satisfied images 53% more often, and images indicating fun 38% more often. The rank-ordered logit model fits reasonably well, with a concordance of 0.792, suggesting it correctly predicts image preference in 79% of cases. Prompt robustness for the rank ordered logit was also evaluated using a the paraphrased and paraphrased plus more explicit prompt versions of the primary prompt. Results for prompt variations of the rank ordered logit were consistent for the survey and neuro measurements, except for the paraphrased version that also showed that

images ranked with Claude 3.5 data were chosen also 3.6% more often (Supplement M).

4.2. Coefficients of variation analysis

Coefficients of variation (CV) are used to show how much the behavioral measures differ within each data source and how consistent these rankings are across survey, neurophysiological, and LLM-based measures. Although the underlying preference data are ordinal, CVs are also applied for the dependent variable in an exploratory manner, treating them as approximately interval-scaled. This allows for descriptive relative comparisons of variability across all measurement methods.

Coefficients of variation indicate how consistently each data source generates image rankings. Regarding the survey-based ratings, the emotional items (e.g., pleased, happy, relaxed) are the most stable, ranging between 8 and 43%, while value items (e.g., beneficial, worthwhile) show a greater spread, ranging between 20 and 48%. Contemplating the ranking of the images, human rank judgments remain moderately volatile (33–78%), peaking for Image 7 and tightening for Image 5, suggesting that consensus is easier to reach on some visual themes than on others.

Neurophysiological data present a different pattern at the image level. Image rankings based on different neurophysiological indicators vary substantially. Rankings based on valence display a high variance (86–334%), whereas engagement, impact, memorization, and workload settle into a more uniform range of 29–88%. These different results show that affective neural responses cause less consistent image rankings than the cognitive neural responses.

LLMs occupy the middle level in terms of image-level consistency. Variability in the rank orders differs depending on the coding. GPT-4o's variability is modest when only nationality is supplied (11–21%). It widens sharply (14–76%) once four contextual cues are introduced. Claude Sonnet 3.5 remains volatile throughout (12–88%). This indicates fundamental differences in how these LLMs process and integrate multiple pieces of information for ranking tasks. Full coefficients of variation distributions are provided in Supplement E.

Fig. 4 illustrates the mean image rank positions for each of the three measurement methods, highlighting the systematic differences between them. Survey, neuro, and both LLM ranks rarely coincide, except for Images 2, 5, and 6. These divergences, coupled with the coefficients of variation results, corroborate Hypothesis H1, which states that different collection techniques yield distinct response patterns when ranking images of different tourism types.

4.3. Cross-method correlations

To demonstrate the correlations between human image rankings,



Fig. 3. Rank-ordered logit estimates with 95% confidence intervals.

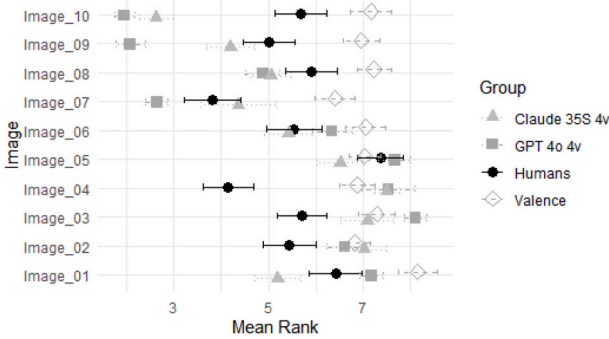


Fig. 4. Mean image rank positions (scale 1 to 10) derived from ordinal ranking obtained from surveyed humans, neurophysiological valence responses, and prompted LLMs.

neurophysiological data, LLM outputs, and human image rankings, we applied the Spearman correlation coefficient and the corresponding p-value (see Fig. 5). GPT-4o and Claude rankings were each considered twice: 1) using only nationality and 2) including the four contextual variables: nationality, age, gender, and prior visitation to the archipelago. For comparative analysis, the valence measure was rescaled. Sub-samples only containing German and Spanish data were also calculated (Supplement F).

In its original form, valence shows weak and sometimes negative correlations (−0.385 to 0.343). Only four images show statistical significance. After rescaling the valence measures, the improvement is visible (0.248 to 0.538): All photos show significance, suggesting valence requires careful calibration for meaningful interpretation. The other neurophysiological data measurements show distinct patterns of correlation strength. By focusing on workload and, therefore, the mental effort needed to process the images, a strong positive correlation with human rankings is evident ($\rho \approx 0.77$ -0.83). Similarly, strong positive correlations are observed for engagement, defined as the degree to which people focus on a stimulus, and memorization, which reflects the strength of the cognitive process involved in forming memories: engagement ($\rho \approx 0.87$ across all images, $p = 0$) and memorization ($\rho \approx 0.80$ -0.83).

GPT-4o and Claude show highly variable performance, suggesting they may be sensitive to specific image characteristics or context. GPT-4o and Claude, with four and one context variables, show a wide variation in their correlation with the image rank. Interestingly, the performance of GPT-4o and Claude shows significant positive correlations for Images 2, 3, and 4 in all LLM options. However, for Images 9 and 10, the LLMs show significant negative correlations. The findings justify a mixed-methods strategy that prioritizes neuro-metrics, treats raw valence with caution, and uses LLM outputs selectively. This improves the precision and efficiency of visual marketing research in tourism and related fields.

These results support Hypothesis H2, which states that image preference rankings are significantly correlated with specific response measures across data collection methods. However, the effects are inconsistent across measurement methods and ranked image types.

4.4. Logistic regression

To understand which measurement method explains the differences in image preference rankings, we used ordered logit models for each image. This image-specific approach allows us to see how predictive effects vary across different tourism types. To illustrate the ordered logit regression analysis results, four images were selected as examples: Image 3, representing cultural vacations, displays a positive Spearman correlation between all LLM and neurophysiological variables; Image 10, representing beach holidays, shows a positive correlation for neurophysiological variables and a negative correlation with LLM variables; and Images 5 (relaxing holidays) and 7 (party tourism) are highest and lowest ranked by participants. The results of the ordered logit model for Image 3 are presented in Table 1.

Effects associated with the country variable should be interpreted as context-bound associations rather than cultural differences.

For the remaining models, tables are provided in Supplement G.

For five of the logistic models, German respondents show higher odds of ranking Image 3 favorably: odds ratios range from 2.8 to 4.8 (Models 1–3, 5: $p < 0.05$; Model 4: $p < 0.10$). Age has a minor marginally significant effect (OR = 1.046, or 4.6% rise per year, $p < 0.10$). For Image 3, 'pleased' (OR = 2.8-3.4) and 'relaxed' (OR = 2.2-2.5) are strong predictors of higher rankings. Several value-based variables,



Fig. 5. Rank correlation matrix, human image rank, i1-i10 (N = 96).

Table 1
Ordered logit models for image 3.

Ordered Logit	i3	cultural				
N=96	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Survey vars.						
country (Ger = 1)	1.57 (0.45) *** [4.81]	1.07 (0.41) ** [2.92]	1.03 (0.51) * [2.8]	1 (0.56). [2.71]	1.57 (0.46) *** [4.79]	0.93 (0.57) [2.54]
age	0.03 (0.02). [1.03]	0.01 (0.01) [1.01]	0.03 (0.02) [1.03]	0.04 (0.02) * [1.04]	0.03 (0.02) [1.03]	0.04 (0.02). [1.04]
gender (W = 1)	-0.58 (0.42) [0.56]	0.15 (0.38) [1.16]	-0.08 (0.37) [0.92]	-0.61 (0.42) [0.54]	-0.25 (0.43) [0.78]	-0.36 (0.44) [0.7]
visited (Yes = 1)	-0.53 (0.44) [0.59]	-0.91 (0.41) * [0.4]	-0.96 (0.4) * [0.38]	-0.57 (0.45) [0.57]	-0.51 (0.45) [0.6]	-0.53 (0.46) [0.59]
pleased	1.12 (0.44) * [3.06]			1.05 (0.47) * [2.84]	1.23 (0.46) ** [3.4]	1.18 (0.49) * [3.26]
satisfied	-0.25 (0.46) [0.78]			-0.09 (0.47) [0.91]	-0.45 (0.47) [0.64]	-0.41 (0.49) [0.66]
happy	-0.54 (0.4) [0.58]			-0.62 (0.4) [0.54]	-0.66 (0.41) [0.52]	-0.7 (0.41). [0.5]
relaxed	0.81 (0.35) * [2.24]			0.78 (0.35) * [2.18]	0.91 (0.38) * [2.49]	0.86 (0.38) * [2.36]
fun	0.6 (0.46) [1.82]					
pleasant	-0.09 (0.4) [0.92]			0.17 (0.37) [1.19]	0.43 (0.37) [1.54]	0.42 (0.38) [1.52]
entertaining	-0.1 (0.35) [0.9]			0.2 (0.35) [1.22]	0 (0.36) [1]	0.19 (0.38) [1.21]
beneficial						
worthwhile						
good-value	0.42 (0.36) [1.52]			0.41 (0.37) [1.5]	0.41 (0.37) [1.51]	0.3 (0.39) [1.35]
quality-price	-0.18 (0.33) [0.84]			-0.03 (0.34) [0.97]	-0.14 (0.34) [0.87]	-0.05 (0.35) [0.96]
Neuro vars.						
valence		0.01 (0) ** [1.01]			0.01 (0) [1.01]	0.01 (0) [1.01]
engagement		0 (0.01) [1]			-0.01 (0.01) [0.99]	-0.01 (0.01) [0.99]
impact		0 (0.01) [1]			0 (0.01) [1]	0 (0.01) [1]
memorization		-0.04 (0.02) * [0.96]			-0.04 (0.02) * [0.96]	-0.05 (0.02) * [0.96]
workload		0 (0.01) [1]			-0.01 (0.01) [0.99]	-0.01 (0.01) [0.99]
LLM vars.						
img rank by claude35 S (given country + age + gender + visited)			-0.08 (0.09) [0.92]	-0.11 (0.09) [0.89]		-0.13 (0.09) [0.88]
img rank by gpt4o (given country + age + gender + visited)			0.18 (0.19) [1.2]	0.03 (0.2) [1.03]		0.02 (0.21) [1.02]
img rank by claude35 So (given country)			-0.09 (0.15) [0.92]	-0.04 (0.15) [0.96]		-0.07 (0.16) [0.93]
img rank by gpt4o (given country)			-0.34 (0.25) [0.71]	-0.56 (0.29) * [0.57]		-0.57 (0.29). [0.57]
intercepts						
1 2	3.91 (1.91) *	-4.81 (1.44) ***	-5.84 (2.76) *	-1.41 (3.34)	1.73 (2.17)	-3.99 (3.57)
2 3	6.59 (1.84) ***	-2.3 (1.25).	-3.39 (2.67)	1.35 (3.28)	4.46 (2.09) *	-1.13 (3.49)
3 4	7.19 (1.86) ***	-1.77 (1.23)	-2.89 (2.66)	1.98 (3.28)	5.1 (2.1) *	-0.45 (3.48)
4 5	7.79 (1.89) ***	-1.26 (1.22)	-2.41 (2.65)	2.62 (3.28)	5.76 (2.13) **	0.24 (3.49)
5 6	8.67 (1.94) ***	-0.54 (1.21)	-1.71 (2.65)	3.54 (3.3)	6.7 (2.17) **	1.18 (3.5)
6 7	9.21 (1.96) ***	-0.08 (1.21)	-1.26 (2.65)	4.11 (3.3)	7.26 (2.18) ***	1.76 (3.5)
7 8	9.74 (1.99) ***	0.35 (1.21)	-0.86 (2.65)	4.64 (3.3)	7.81 (2.2) ***	2.32 (3.51)
8 9	11.32 (2.06) ***	1.75 (1.24)	0.43 (2.66)	6.2 (3.34).	9.46 (2.26) ***	4.01 (3.53)
9 10	12.93 (2.14) ***	3.29 (1.33) *	1.95 (2.7)	7.83 (3.38) *	11.11 (2.32) ***	5.74 (3.56)
coef (std.error) sig [Odd Ratio]						
McFadden_R2	12.7%	7.73%	5.77%	13.56%	14.66%	16.07%

such as 'beneficial' and 'worthwhile,' were excluded due to collinearity. The neurophysiological variable of memorization emerges as consistently significant (OR = 0.96): each one-unit increase decreases the odds of higher ranking by 4%, indicating higher memorization associates with lower image scores.

For Image 3, the McFadden R² shows Model 6 (all data types) has the highest explanatory power (16.07%), followed by Model 5 (survey and neural data, 14.66%). Model 3 (LLM-only) exhibits lower explanatory power (5.77%), indicating that while LLM data contributes some value, combining survey and neurophysiological measurements offers the most effective predictive approach. However, many variables included in the models are not statistically significant. For Image 3, the strongest predictors are feelings of pleasure, relaxation, and memorization, while LLM play a marginal role.

Respective the explanatory power, some R² values appear low. However, this is typical for ordered logit models and behavioral data (Lacy, 2006). As Hair et al. (2019) and Cohen et al. (2003) note, even modest or very small R² values can be meaningful and provide scientifically and practically relevant insights, especially in complex psychological contexts.

For Image 5 (relaxing holidays), among survey items, 'good value' is a dominant driver (OR = 2.15–2.57), together with pleased (OR = 3.06–3.46) result in the richer models. Country based GPT4o's score is positively associated with rankings (OR ≈ 1.47). Overall, value perception and the country-aware LLM metric explain most of the

variance, while neural signals contribute minimally.

For Image 7 (party-holiday), the model fit is driven by survey data. The full model (Model 6) has the highest McFadden R² value (0.227), closely followed by the survey and neural model (Model 5, 0.225). By contrast, the LLM-only model is almost uninformative (Model 3, R² = 0.008), and its coefficients are not significant. Gender is the lone robust demographic effect, with women assigning lower rankings (OR ≈ 0.26–0.29). Among survey items, 'happy' is the strongest predictor (OR ≈ 3.06–3.18), and marginally significant 'entertaining' (OR ≈ 1.9), and 'quality-price' (OR ≈ 1.5). Neural valence, remains significant only in Model 2; other neural metrics (engagement, memorization, workload) are non-informative.

Also, in the case of 10 (beach holiday), the full model explains the most variance (McFadden R² = 0.187), only slightly ahead of the survey and neural model (0.162). The LLM-only model shows a weak explanatory power (0.035). Women give lower rankings (OR ≈ 0.32–0.4). Survey items dominate with 'pleased' (OR ≈ 3.1–3.5) and 'good value' (OR ≈ 2.5–3.2) being consistently positive. Of the neural metrics, only valence is significant (OR ≈ 1.02); engagement, impact, and workload are inert, except for marginally significant memorization (OR ≈ 0.97). LLM features scarcely help: Claude's country-only score is negatively signed (OR ≈ 0.53). Overall, emotional and perceived value, not LLM output or other neural measures, drive the rankings.

Fig. 6 shows that the model fit peaks for Images 6 and 7 (McFadden R² = 0.221–0.227) and bottoms out for Image 1 (R² = 0.12). Neural

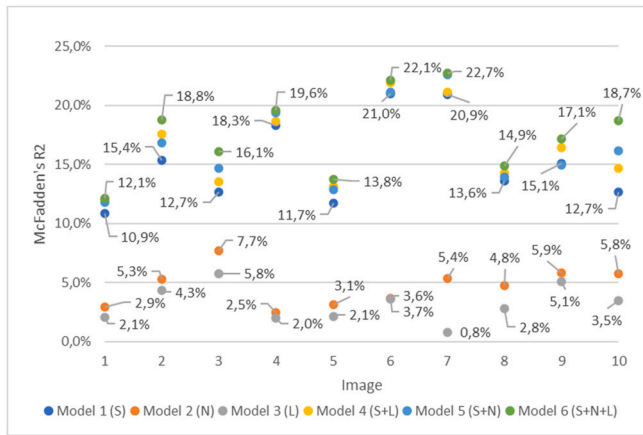


Fig. 6. McFadden's R-squared for each model and image.

signals boost prediction most for Images 1, 3, and 10, whereas LLM scores add value primarily for pictures 2, 5, and 9. Emotional-survey items are helpful across the board, with the strongest results for Images 7 and 10, and weakest for Image 1.

As a baseline, Model 0 was calculated, which incorporated only the four contextual variables. Model 0 shows (see Supplement I) a low contribution ranging from negligible (i7 and i10) to small but appreciable (i8 with 0.024, i2 with 0.026, i9 with 0.031, and i4 with 0.049). Overall, these theme-dependent patterns suggest the need for image-specific measurement approaches.

Prompt variations for Model 6 ordered logit were also evaluated using a the paraphrased and paraphrased plus more explicit prompt versions of the primary prompt. These variations results were consistent for the three types of measurements across image models (Tables M1 to M10, Supplement M).

These findings support hypothesis H3, suggesting that a multi-method approach, which combines various data sources, predicts tourism image rankings more effectively than any single method alone.

We assessed the robustness of the predictor findings by comparing results across the rank-ordered logit model and the image-specific ordered logit models (see Supplement D and M). Across model specifications, survey-based affective responses (especially pleased and relaxed) and selected value items (e.g., beneficial) show the most consistent positive associations with earlier higher-ranking preference. The EEG-derived valence index also contributes to the rank-ordered framework and appears more salient for certain tourism types in the image-specific models. In contrast, LLM-derived measures cannot be used as robust predictors: they are generally non-significant in the rank-ordered logit specification, but isolated associations in image-specific models contribute to the explanatory power of the observed assessment, with heterogeneity across tourism types. Overall, conclusions are stable across modeling choices, increasing confidence that the findings reflect the value in the distinct data types to contribute to the explanation of tourism preferences.

4.5. Contextual demographics and emotional versus cognitive considerations

The analysis shows that visual preferences are strongly conditioned by demographic context. Country of residence, for example, distinguishes several images: Spanish participants systematically assign higher ranks to the health-vacation scene (Image 9, OR = 0.16), whereas German respondents favor the cultural-holiday vignette (Image 3, OR ≈ 2.7-4.8 for Models 1-5). Gender patterns are equally pronounced, with men consistently giving higher ranks to images centered on activity, adventure, party life, and nature (Images 2, 4, 7, 8, 10 OR = 0.21 - 0.39). Age effects run in parallel but in the opposite direction for different

themes: older adults prefer adventure and nature options (Images 4, 8), while younger participants choose toward the more dynamic options (Image 2). Prior experience with the destination also matters; repeat visitors down-rank gastronomic and health images (Images 1, 9), whereas first-time visitors give higher rankings to the active-holiday frame (Image 2). Taken together, these findings, illustrated in Fig. 7 and detailed in Supplement L, highlight the situational nature of visual appeal across demographic groups.

Emotional responses prove more predictive power than cognitive or value-based judgments. Across all images, survey emotional variables (pleased, happy, relaxed) consistently demonstrate stronger effects than cognitive/evaluative variables (value-based, beneficial, worthwhile, quality-price) (Supplement H). Neurophysiological evidence converges on the same conclusion: valence, an affective index, predicts rank in several models (see Image 10), while cognitive workload shows only sporadic influence. The exception is memorization, which demonstrates significant effects for Images 1 and 3, indicating that some cognitive measures still play an important role. Overall, the data show that emotions are the primary factor in explaining image preferences. However, the data also reveal that selected cognitive processes still contribute to image preferences in specific contexts. This suggests that cognitive processes play a complementary role rather than a purely subordinate one.

5. Discussion

This investigation, which uses three methods to evaluate tourism destination images, advances tourism research by integrating traditional survey-based methods with neurophysiological and LLM-based assessment techniques. This approach yields richer insights into tourists' decision-making processes than traditional single-method approaches (Bastiaansen et al., 2022; Li et al., 2023) and allows for a more comprehensive way of understanding how conscious and unconscious processes influence tourists' preferences and value perceptions.

Building on dual-process theory as a conceptual foundation for information processing and preference formation, this study leverages the additional explanatory power of neurophysiological measurements, which capture dimensions of human response not accessible through survey methods, and incorporates an LLM-based assessment perspective that complements human information processing. In line with recent research emphasizing the growing role of artificial intelligence in shaping and enhancing human decisions (e.g. Ahmad & Mir, 2025; Arora et al., 2025) and highlighting the value of neurophysiological measures in understanding affective and cognitive responses (e.g., Bastiaansen et al., 2022, 2024), our findings illustrate how integrating multiple data sources: subjective self-reports, physiological responses, and LLM-based evaluations, provides additional explanatory depth and enriches understanding of tourists' decision-making processes, overcoming the limitations of traditional single-method approaches.

This supports earlier calls for research indicating that self-reported

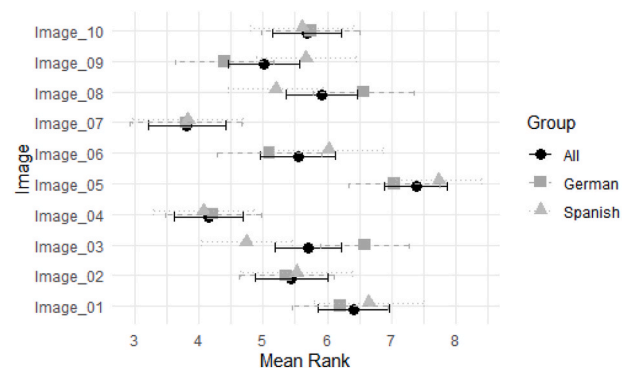


Fig. 7. Mean image ranks by nationality. Error bars denote ±1 SE.

data alone is not able to fully detect unconscious reactions (e.g., [Deng & Chen, 2023](#)). It indicates the importance of bridging physiological and behavioral indicators to minimize the gap between automatic and controlled processes. The proposed triangulation of measurement methods for assessing consumers' image, with survey data, neurophysiological data, and LLM assessments, allows us to observe and integrate different aspects from both systems.

To summarize, this three-dimensional approach leads to a more holistic understanding of the destination image perception and consumer behavior, linking emotional and cognitive reactions to a contextual interpretation. Thereby, these findings enhance theoretical discussions in tourism research by applying the dual process theory in a multimodal data setting.

5.1. Theoretical implications

This study contributes to the ongoing debate on assessing destination attractiveness by proposing a three-method approach that employs dual-process theory as a conceptual lens. The empirical findings are interpreted cautiously through this functionalist lens to organize and interpret the integration of survey data, neurophysiological measures, and LLM-based image analysis. Specifically, neurophysiological measurements of emotional valence and engagement function as fast-affective correlates consistent with System 1 processing, in line with [Bastiaansen et al. \(2022\)](#) and [Li et al. \(2022\)](#). This alignment suggests that tourism images showing gastronomic, active, relaxing, and party tourism themes (which are significantly influenced by both of these measures) rely on rapid, intuitive assessments.

Conversely, memorization and working memory act as more effortful cognitive correlates aligned with the deliberative processing of System 2 ([Michael et al., 2019](#)), which is slower and requires greater cognitive effort. While our results indicate that these cognitive measures influenced responses across all images, their effect appears stronger in adventure, party, and health-related tourism themes. Importantly, high memorization values do not necessarily indicate positive values; in emotionally driven contexts like beach or party tourism, strong cognitive processing may actually be disturbed by intuitive emotional responses.

This integrated perspective captures the multidimensional nature of consumer preferences in tourism by providing insights into patterns associated with System 1 (emotional, intuitive) and System 2 (deliberative, analytical) processes in decision-making. Our findings further show that each method captures distinct aspects of affective-cognitive evaluation ([Zhan et al., 2024](#)). Surveys engage both systems but show limited variability, while neurophysiological measures detect emotional reactions that self-reports may overlook, confirming their reliability as indicators in tourism marketing ([Li et al., 2022](#)). The high variability in neural valence reflects rapid, emotion-driven responses (System 1), particularly for beach or party tourism images, where strong affective reactions can lower preference rankings. In contrast, higher memorization values, linked to reflective, cognitive processing (System 2), enhance preferences for cognitively oriented contexts, such as cultural or gastronomic tourism. Hereby, it is important to mention that high memorization levels do not necessarily indicate positive values. In case of images showing high emotional contexts, such as beach or party tourism pictures, a strong cognitive processing may be disturbed by intuitive emotional responses. This, in turn, leads to lower preference rankings. In the case of images, when showing cognitively oriented contexts (e.g., cultural or gastronomic tourism), memorization contributes to a reflective understanding, and a high value tends to enhance the preference to participate in this travel type. Whether the memorization effect is positive or negative is not contradictory; it rather depends on the context.

LLM-based assessments provide a complementary, machine-derived perspective on consumer choice, revealing differences in how synthetic models approximate human intuitive and analytical reasoning,

and humans increasingly rely on such systems for decision support. They show improved performance with relaxing holidays (Image 5), where evaluations depend more on the analytical System 2 (good-value) than on System 1 responses.

The limited previous literature that uses experiment-based neurophysiological studies focusing on touristic-relevant content examines emotional and cognitive responses to destination marketing ([Bastiaansen et al., 2022](#); [Deng & Chen, 2023](#)), hotel selection processes ([Fronza et al., 2021](#)), and cultural experiences ([Strijbosch, 2022](#)), sometimes combined with interviews ([Bastiaansen et al., 2024](#)). To our knowledge, this represents one of the earliest empirical integrations of synthetic image assessment with survey and neurophysiological measurement methods in tourism research. Overall, this work emphasizes that emotional and cognitive factors contribute differently depending on the tourism theme. This highlights the need for context-specific approaches in destination image evaluation. This integrated approach, which uses dual-process theory as a conceptual framework for interpreting how different methods capture intuitive versus deliberative processing, deepens the understanding of how tourists perceive, evaluate, and prefer destination images.

5.2. Practical implications

The findings of this investigation have important implications for tourism marketing and research methodology. Rather than advocating universal adoption of integrated approaches, we offer context-specific guidance to help destination management organizations and tourism practitioners determine when each measurement method provides sufficient value to justify its costs and limitations. The varying effectiveness of different methods for different image types indicates that measurement strategies should be tailored to specific tourism types. The results also highlight the potential of neurophysiological measurements to provide unique insights while suggesting caution in applying AI-based assessments in tourism image evaluation.

Marketers in the tourism industry, including destination management organizations and practitioners, are recommended to use multiple data sources. Although they are expensive and difficult to implement, neurophysiological measures are especially valuable for pre-testing emotional sensitivity before costly rollouts ([Bastiaansen et al., 2022](#); [Deng & Chen, 2023](#)). Our results demonstrate that neural valence captures emotional responses that self-reports overlook, especially in response to emotionally charged imagery, such as that associated with beach tourism. EEG also provides unique predictive value for tourism types where unconscious emotional reactions strongly influence preferences, including health offerings. Meanwhile, LLM assessments show promise for mainstream tourism products ([Goyal & Mahmoud, 2024](#)). LLM-based assessments offer efficiency gains through rapid evaluation at minimal cost, but our findings reveal important limitations. Our research shows that for active and health holidays, the demographic-aware Claude model demonstrated positive associations with human rankings. For the country-aware GPT model positive associations with human rankings were found for holidays, as well as for the country-aware Claude model with positive associations for beach holidays. LLMs may be suitable for initial screening of large image libraries, generating hypotheses for subsequent human testing, or supplementing limited survey samples in contexts with limited resources. However, our results indicate variability in LLM performance across image types and prompt configurations. LLM assessments should not serve as the sole basis for significant marketing decisions. The architecture and training data of these systems differ from human cognition, and any extrapolation of behavioral theories to synthetic responses requires empirical validation.

Tourism boards and DMOs can create personalized marketing campaigns that target the right audiences with appropriate stimuli by combining the results of the different methods in their marketing strategies. These campaigns can be made appealing, competitive, and

convincing (Hou & Pan, 2023). They can influence an individual's emotional arousal, capture customers' attention, and lead to a high conversion rate (J. Lee & Hong, 2016). Innovative and effective strategies may incorporate different data sources to assess customers' willingness to pay, such as factors measured using an EEG helmet (Li et al., 2022). However, DMOs considering integrated measurement approaches should be aware of several risks that accompany multi-method adoption. Combining methods may compound rather than correct biases if the sources share systematic errors. The rapid evolution of generative AI means that LLM-based assessments may yield different results as models are updated, so organizations should document model versions and consider periodic recalibration. The apparent precision of neurophysiological and AI-based metrics may also encourage overconfidence in findings that reflect specific experimental conditions rather than generalizable preferences, since laboratory settings differ meaningfully from actual travel planning contexts. For many DMOs, well-designed surveys capturing emotional and value-based dimensions may provide adequate insight at substantially lower cost.

Some of the observed differences between the two samples may reflect variation across market contexts rather than stable cultural differences. Prior research and market studies document heterogeneity in travel-related preferences across these visitor markets, for example, with respect to the relative popularity of different types of travel (FUR/ForschungsgemeinschaftUrlaubundReisene.V., 2024a; FUR/Kompetenzzentrum Tourismus, 2024b; Ministerio de Industria y Turismo, 2023; Turespaña, 2025). These findings provide contextual background but do not allow causal attribution to culture in the present study.

5.3. Limitations and future research

This study has several limitations that create opportunities for future research. First, the neurophysiological component used EEG, which includes data from only 96 participants. Such small sample sizes are common in EEG studies but restrict statistical power and generalizability to the population (Li et al., 2022, 2023).

Second, our study employs a bi-national, cross-market design, with participants from Germany and Spain. This approach enables comparative insights across two major visitor markets but does not constitute a causal cross-cultural analysis. Moreover, the data were collected in 2022 in Germany and in 2023 in Spain, which may cause temporal or contextual effects that cannot be fully separated from cross-market differences. Future research should include multiple countries and data collected in the same year to provide more generalizable data.

Third, laboratory conditions differ significantly from holiday-planning contexts. While controlled settings help isolate neural signals, they may also dampen spontaneity and alter decision-making strategies (Winkler & Murphy, 1973). Technical caveats persist as well. EEG cannot pinpoint the precise cortical source of a signal (Boksem & Smidts, 2015), which makes it difficult to cleanly map activity onto Dual-Process Theory's System 1 versus System 2. Consequently, given the novelty of integrating different, complementary data types from surveys, neurophysiological measures, and LLMs, our findings should be viewed as exploratory. The neurophysiological metrics utilized rely on vendor-defined composite indices computed by proprietary software, which are treated as relative indicators of engagement rather than direct measures of localized neural activity. Because the dual-process framework is applied here as a functionalist conceptual lens for organizing these diverse data types, rather than as a mechanistic claim of mental function, alternative theoretical explanations for the observed response patterns may exist. Furthermore, EEG data collection is labor-intensive, requiring approximately 1 h per participant, which further limits large-scale deployment. Moreover, EEG technology can be very cost-intensive in terms of acquisition and training, and hence may be a barrier for adoption. It is considered profitable, especially in the context of emotionally strong tourism marketing strategies.

Furthermore, the LLM component presents its own set of issues. We

only tested two prompts (one with four contextual cues) and two models (GPT-4o and Claude 3.5 Sonnet). Image order effects and the models' internal reasoning paths require systematic sensitivity checks. Future studies should expand the scope to include other generative models, richer profiling data, and, crucially, newer LLM versions, as their rapid evolution may substantially impact predictive accuracy. Finally, all responses were driven by a single set of visual stimuli. Although exogenous forces such as economic conditions, competing destinations, and current travel trends were not modeled, they likely influence real-world choices. Closing these gaps with larger and more diverse samples, in-situ or VR-based experiments, multimodal biometric inputs, complementary survey variables (like pull/push motivations, engagement dimensions, attitudes/congruence, among others), and continuously updated AI engines will strengthen the explanatory power of the triple-method approach and clarify the best ways to integrate LLMs into tourism research.

6. Conclusion

The proposed triple-framework for measuring tourism preferences shows how integrating neurophysiological, self-reported, and AI-generated data can provide a more comprehensive understanding of how tourists process information and evaluate destination images.

Each approach provides correlates for distinct dual-process dimensions: surveys reflect both System 1, or emotional, and System 2, or deliberative responses; neurophysiological data indicates unconscious affective reactions that are overlooked in self-reports; and LLM assessments offer synthetic evaluations approximating analytical reasoning and accounting for the increasing use of LLM as a 'third system' for tourists decision support. The improved performance of integrated measurement models compared to single-method approaches highlights the importance of methodological triangulation, especially since effectiveness varies across the tourism type under consideration, ranging from emotionally driven beach tourism to cognitively oriented cultural experiences. This contributes to the application of dual-process theory as a conceptual framework by empirically demonstrating how conscious and unconscious processes complement each other in preference formation. For destination management organizations, findings suggest effective image evaluation requires tailored measurement strategies aligned with specific tourism types. This integrated approach proposes a methodological advancement in tourism research, bridging traditional surveys with emerging neuroscientific and AI applications to capture the multifaceted nature of destination image perception and tourists' preference formation.

CRedit authorship contribution statement

Kathrin Jaszus: Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Anett Erdmann:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Jose M. Ramos-Henriquez:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation. **Jose M. Mas-Iglesias:** Resources, Data curation.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jdmm.2026.101089>.

Data availability

Data will be made available on request.

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