AI-Driven Facial Emotion Analysis for Customer Emotion Recognition - an explanatory study

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Abstract. Facial Expression Analysis is a method that, while often mentioned, is rarely applied in marketing research literature. With the introduction of widely accessible AI tools, employing this method may provide valuable insights into the reception of a presented product. In this article, a commercial FEA tool was used to examine the emotional responses of respondents to 100 images of hotel rooms. The tool and method used are discussed in detail, evaluating their usefulness for this type of research without the need for specialized equipment. The method described in this study does not require personal contact, and the research can be conducted online. Based on the analysis of the results, it was determined which images of hotel rooms elicit positive emotions among the participants.

Keywords: facial expression recognition, facial expression analysis, tourist product presentation

1 Introduction

Currently, an increasing number of companies are adopting solutions based on artificial intelligence (AI). This trend is gradually transforming traditional service delivery methods by employees into technology-driven models [1]. AI has become an integral part of everyday life significantly influencing production methods, lifestyles, and communication within society, and is contributing to the transformation of society as a whole [2]. It is anticipated that in the coming years, emotional artificial intelligence will begin to play a significant role in daily life, integrating with technologies such as virtual assistants, vehicles, and mobile devices [3]. Emotion recognition systems are currently being applied in various fields, including education, business, marketing, medicine, public safety, and human resource management [3, 4]. However, it is notable that the most dynamic development of AI is occurring in the commercial sector [5]. In scientific literature, there are numerous technical studies dedicated to AI models, including those for emotion detection. However, the number of scientific studies focused on the implementation of emotion recognition methods in the field of marketing or addressing AI from a management perspective is limited.

People typically make decisions unconsciously, guided by emotions [6], which highlights the importance of emotions in the decision-making process [7], particularly in the case of leisure-related services (such as hotel bookings and tour purchases) [8]. Research has emphasized the impact of positive emotional stimuli on intentions to book

hotel stays [9, 10]. Photographs can stimulate the imagination by contributing to the visualization of potential experiences [11], which may ultimately lead to specific behavioral responses [12], such as booking a particular hotel. This study aims to determine whether it is possible to use a commercial tool like Morphcast SDK AI to identify images that evoke more positive emotions, and thus contribute to a better perception of the hotel facility by customers, and whether it is possible to identify common elements of these photographs.

Therefore, this article poses the following research questions:

- RQ1: Can the Morphcast tool be used to identify images that evoke positive emotions?
- RQ2: Is it possible to identify common elements among images that evoke positive emotions?

Paper presents the theoretical background related to artificial intelligence for facial emotion recognition, the application of emotion analysis in marketing research and aspects of effective photography. Subsequently, the research methodology employed and the results obtained are described. The article concludes with findings and discussion, as well as directions for future research and the limitations identified during the research process.

2 Theoretical background

Facial expressions play a crucial role in non-verbal communication, enabling the conveyance of complex mental states during interpersonal interactions, with the face itself is the main medium for expressing emotions [13]. Emotions help to communicate with the external world [4] and have a significant impact on the way consumers process information and make purchasing decisions. Products that enhance positive emotions can increase consumer purchase intentions [14]. Understanding these emotions can help increase the effectiveness of marketing activities [15]. The field known as "Emotion AI" or "Affective Computing" has been evolving since 1995, and focuses on interpreting, understanding, and even replicating human emotions [16]. Currently, this field is undergoing dynamic growth [5], with research into emotion recognition through facial analysis gaining popularity due to its potential applications in areas such as healthcare, education, security [17] and marketing [18].

Emotion recognition using visual technologies is a research area focused on developing algorithms that can automatically identify emotions based on facial expressions which can be detected and analyzed using computer vision tools [19]. Machine learning techniques for facial emotion recognition enable the processing of this information into conclusions about an individual's emotional state [16]. The foundation of any face recognition system is the encoding of micro-movements [20] controlled by facial muscles [21] which contribute to the generation of numerous communicative signals [22]. The movement of specific points on the face is then computed, allowing for facial recognition and the analysis of its expression [23]. Facial Expression Recognition (FER) refers to the technology used to analyze facial expressions to identify emotions, while Facial Expression Analysis (FEA) pertains to the techniques and processes used

to analyze emotions expressed through facial expressions and understand subtle expressions that can be detected through algorithms [24]. An emotion recognition system detects a face, extracts features characteristic of a particular emotional state [25], and then analyzes them to determine the most probable emotion [26]. Commercial AI systems used for emotion analysis often employ Ekman's typology, which assumes six basic emotions: happiness, surprise, fear, sadness, anger, and disgust [27].

The importance of visual perception has contributed to the spread of research examining the impact of visual product presentation on commercial outcomes [28]. In recent years, both machine learning (ML) and artificial intelligence (AI) have gained widespread interest in a variety of industries, including marketing. Among the implemented solutions are customer-greeting robots, big data analysis for price adjustment and prediction, recommendation systems for product and offer personalization, natural language processing to enhance customer engagement and interaction, and improve shopping experiences, as well as emotion analysis for monitoring customer satisfaction [29]. Commercial access to artificial intelligence enables companies to create algorithms that support their business strategies, such as recognizing human behavior or making decisions [24]. The prevalence of AI for emotion analysis is evidenced by the fact that most leading technology companies, such as Google, Amazon, Microsoft, and IBM, offer cloud-based services that allow the creation of applications supported by AI-driven emotion analysis [5].

2.1 Application of emotion analysis in marketing research

Facial expression-based emotion recognition has recently gained various fields, including healthcare, education, the labor market, entertainment, and leisure activities. In marketing, it plays a significant role in analyzing consumer behavior, purchasing habits, advertising, and social media engagement.

Emotion analysis can be used in assessing general reaction to multimedia content [30] or willingness to take risks [31]. Emotions have been analyzed in relation to the product itself and associated stimuli [32], general consumer purchasing behavior and purchase intentions [33] and the perception of luxury in the context of scarcity effects [34]. Research has explored price variation and customer loyalty in response to emotional reactions to inconsistent product pricing on different websites [35], trust, emotions, and purchase intentions in high- and low-risk online pharmacies [36] as well as the attractiveness of websites in terms of evoking emotions – for specific products such as coffee [37] or social campaigns like anti-tobacco advertisements [38].

In the area of consumption, emotion analysis has been utilized in studies on the development of food and beverage products [39], sensory evaluation of food in general [40] and specific examples such as wine [41], the enjoyment of food and drink [42], external aspects of food products [43], and their packaging [18] related to associations, product acceptance and latent intentions [44].

Emotion analysis is used in advertising in terms of its overall effectiveness [45], and in relation to specific types of advertising. Studies have been conducted on the real estate industry [46], analysis of painkiller packaging [47], negative political ads [48], gun violence prevention announcements [49] and reactions to YouTube advertisements according to gender identity [50].

In social media, facial expression analysis has been compared with linguistic analysis, such as comments or emojis [51]. Facial expressions and moods have also been examined in relation to influencer reviews [52]. Emotion analysis has been discussed as a method for detecting deepfake [53], analyzing facial expressions in chatbot content formats [54] and general issues concerning facial expression analysis for multimedia services quality in wireless networks [55]. Furthermore, user experience (UX) has been assessed to develop higher-quality and more efficient digital services [56] as well as the visual appeal of graphs depicting household energy consumption [57].

2.2 Key aspects of effective photography

To gain a competitive advantage, hotel service providers strive to create the best possible impression of the services they offer [58]. The intangible nature of the product is significant because potential customers cannot assess the property before arriving. As a result, evaluations are often based on images available online [59]. Neuromarketing research has shown that the human brain processes visual content 60,000 times faster than text-based information [60]. Furthermore, the majority of the global population are visual learners [61]. Therefore, digital images of hotels placed online should communicate to customers physical proof of the value the service being offered [62].

Photographs help consumers to visualize destinations and to perceive the offer more clearly and accurately. The way customers perceive specific products directly influences their tourism services purchasing decisions [63]. In online marketing, hotels typically use the following types of shots to present the facility: hotel room (living room, bedroom, bathroom), lobby, entrance, hotel facilities and services, conference rooms, and the hotel's surroundings [64]. Customers tend to respond more positively to images with more natural light. Shots taken from different angles create the impression that the property is presented comprehensively. The composition and aesthetics of the photographs are also important. Additionally, images of the entrance, patio, and surrounding views are highly appreciated [65]. Hotel properties with warm-toned images are more frequently booked than those with cooler-toned photos [66]. Professional photos of hotel properties are perceived as more attractive than amateur ones, and the attractiveness of photos influences the intention to book the property [67]. An excessive number of photos may make browsing hotel websites more difficult and thus negatively affect booking decisions [68]. Therefore, it is important to select appropriate images that will generate the most interest from potential customers.

Cuesta-Valiño et al. [69] identified the determinants of the best rated photographs. They should show the rooms in a way that makes them appear spacious. The authors suggest avoiding the presence of people in the photos (as it hinders the viewer's ability to imagine themselves in the space), with the exception of hotel staff in uniform. Lighting (and the time of day) are not crucial, but the photo should be aesthetically pleasing and highlight the room's best features (e.g., electric lighting if it enhances the room's ambiance or natural light if it shows the room well on a sunny day). Additionally, if there is an attractive view outside, it should be included in the photo. The authors also recommend highlighting visually appealing details through close-ups of unique elements. In the case of bedrooms, the best-rated images are those without people, with subtle color schemes, taken at an angle in daylight.

3 Method

This study used the MorphCast Emotion AI HTML5 SDK tool, which is built as a JavaScript API based on deep neural networks [70]. This tool was integrated into a specially prepared website utilizing WordPress on the SSL-protected web host, displaying images using Lightbox (https://srv42257.seohost.com.pl/research). A total of 100 images depicting the bedroom areas of hotel rooms from various perspectives were selected for the study: images showing the bed from the front (10 images), from the side (10 images), from behind the bed (10 images), in close-up (10 images), with people present (10 images), angled shots in close shot (20 images) and long shot (20 images), as well as images focusing on elements other than the hotel bed (10 images), sourced from Booking.com. The images depict properties located in coastal resorts in Poland. The greater number of angled shots chosen for the study is because these shots are the most popular on booking platforms and are also highly diverse (differences include lighting, the view outside the window or lack thereof, additional furnishings, and other elements). All elements extracted from the images are:

- Light (natural, artificial, both, difficult to determine)
- Brightness of colour scheme (bright colours, medium colours, dark colours)
- Color tone (warm colours, cool colours)
- Color accents (distinct accents, subdued)
- Presence of accessories, such as towels, glasses, and others (present, absent)
- Window in the image (present, absent)
- View outside the window (visible, not visible, visible but blurry)

The MorphCast Emotion AI HTML5 SDK tool records events using the user's camera, with all information displayed in the browser's console. The tool is activated by a start button, after which the user is prompted to consent to the use of the camera. Upon activation, the user is shown an image labelled as index 0, containing brief instructions for the study: “watch the images of hotel rooms, spend approximately 5 seconds on each image, and consider whether you like the place”. Additionally, the introductory image included a brief explanation of how the study is conducted meaning that the user’s facial micro-expressions will be analyzed by AI using the camera. The researcher provided also a brief tutorial on how to use the tool. The study was conducted either with in-person assistance or through a virtual meeting on Google Meet (with the participant's camera on the video conference being turned off to allow using the camera for conducting research).

As indicated by the tool's documentation, "events are triggered an average of 10 times per second on mobile devices and up to 30 times per second on desktop computers" [70]. In each case, the study was conducted using a computer. The experiment involved 14 deliberately selected participants, all of whom were Caucasian women aged 35 to 45 years from Poland. They had higher education, were employed in intellectual work, had similar median incomes, and lived in urban areas.

The tool displays events in an aggregated form, presenting the following values: average, min, max, last and the number of samples that were used to display the result of a given event. The first values indicated are arousal (in the range [-1.0, 1.0], which represents the smoothened degree of engagement or disengagement) and valence (same

range, which represents the degree of pleasantness, or unpleasantness). The facial arousal values are additionally detailed by the parameters affects38 (probabilities of 38 influences in the range [0.0, 1.0], including such variables as Afraid, Amused, Angry, Annoyed, Bored, Calm, Uncomfortable and others) and affects98 (probabilities of the 98 affects in the range [0.00, 1.00], containing all affects38 variables and 60 others). All variables that can be used are described in the documentation on the website [70].

Only the output of the emotion prediction was used in this analysis. It constitutes a summary of all component variables (affects98) along with the values of the probability distribution of emotions: Angry, Disgust, Fear, Happy, Sad, Surprise and Neutral (The six basic emotions according to the original version of Ekman's theory [27], along with Neutral, which corresponds to an emotional state characterized by the absence of a distinct emotional response). As the tool documentation indicates: “the sum of all the probabilities is always 1, each probability in the distribution has a value between 0 - 1” [70].

The data were collected in the form of text files as console logs. They were then imported into an Excel file, where they were processed using a VBA script that automated the data-cleaning process. Only the values of emotions labelled as *emotion_name* along with their corresponding values were extracted and transposed.

The console log files and the Excel files containing the cleaned data and analysis results have been uploaded to the Zenodo repository at the following address: www.zenodo.com/anonymous.

4 Results

The data were analyzed using MS Excel and PS Imago Pro 10.0 with SPSS 29. In the first step, individual respondents' attitudes were analyzed, followed by the analysis of the emotional responses to the photos. Different respondents expressed emotions with varying intensities. For some, the maximum values achieved were significantly different from others, likely due to differences in facial expression intensity or level of engagement. Generally, it was possible to identify three dominant emotions for each participant. The dominant emotions included Sad (9 times), Happy (9 times), Neutral (8 times), and Disgust (7 times). A detailed analysis of why certain emotions prevail among selected respondents would require additional research, such as in-depth interviews accompanying the experiment. Some participants noted that they were initially stressed by the fact of participating in the study. The dominant emotional reaction may also be influenced by the respondent's current mood at the time of the study.

To verify whether the data followed a normal distribution, Shapiro-Wilk normality tests were conducted. A very low Significance p-value (< 0.001) was obtained, indicating strong statistical evidence against the null hypothesis, which assumes that the data are normally distributed.

The emotional index values for each photo were collected from 14 respondents (with 100 photos analyzed for 13 respondents and 95 photos for one respondent). The total number of emotional readings is n=1395. Descriptive statistics for each emotion (across all respondents and all photos) are presented in Table 1.

Table 1. Descriptive statistics for the variables

	N	Min	Max	Avg	SD
emotion_Angry	1395	0	0,565	0,06824	0,070269
emotion_Disgust	1395	0	0,7	0,11889	0,116908
emotion_Fear	1395	0	0,207	0,04091	0,036182
emotion_Sad	1395	0,01	0,877	0,31479	0,180607
emotion_Surprise	1395	0	0,577	0,07335	0,094639
emotion_Happy	1395	0	0,906	0,12047	0,159351

To determine which photos elicited the strongest emotional responses, quantiles were first calculated to divide the dataset into four parts. Based on the calculated 75th percentile values, variables were created to indicate whether the emotional response to a particular photo exceeded this threshold. These variables were named "s_EmotionName" and were assigned a value of 1 when the emotional response in a given case exceeded the upper quartile threshold. Next, cross-tabulations were used to determine which photos most frequently received a value of 1 for each "s_" (strong) variable corresponding to each emotion. The maximum number of strong emotional reactions recorded for each emotion about individual photos are as follows: s_Angry: 7, s_Disgust: 8, s_Fear: 6, s_Sad: 6, s_Surprise: 6, s_Happy: 6, s_Neutral: 6. Table 2 highlights the photos that triggered a strong emotional response in 5 or more cases.

Table 2. Photos elicited the strongest emotional responses

emotion	s_Angry	s_Disgust	s_Fear	s_Sad	s_Surprise	s_Happy	s_Neutral
photos number	19, 20, 25, 27, 28, 29, 35, 41, 51, 59, 88	17, 18, 19, 28, 36, 41, 42, 61, 64, 65, 77, 81, 82, 94, 98, 99, 100	2, 6, 19, 38, 44, 45, 46, 47, 49, 59, 61, 75	22, 34, 43, 55, 56, 57, 58, 70, 74, 75, 76, 79, 80, 86, 89, 91, 92, 94	1, 24, 30, 34, 38, 39, 45, 51, 58, 59, 60, 61, 68, 70, 82	4, 7, 8, 9, 11, 12, 13, 14, 20, 30, 31, 36, 40, 41, 48, 52, 69, 74, 75, 90, 95	6, 33, 35, 39, 50, 54, 64, 68, 71, 72, 77, 78, 80, 81, 85, 87, 91, 100
n	11	17	12	18	15	21	18

For 28 photos, strong emotional reactions were recorded in 5 or more than instances. The most frequently associated emotions were: s_Disgust and s_Neutral (4 times), s_Angry with s_Disgust (3 times), and s_Sad and s_Surprise (3 times). For 54 photos, one strong emotion was recorded, which appeared in 5 or more respondents.

In the next step, the analysis of the photos was conducted. The photos were categorized based on the type of lighting, brightness, colour tone, presence of distinct colour accents, presence of accessories, windows, views outside the window, and type of shot.

Initially, the type of lighting in the photos was analyzed and distinguished as natural, artificial, and both. Photos that used natural light were classified as those where sunlight is visible and lamps are not turned on. Photos with artificial light were those where lamps were on, but no sunlight was identified. If both sunlight and lit lamps were visible, the photo was classified into the "both" category. In total, it was found that 40 photos featured artificial light, 40 photos featured both types of light, and only 20 photos were taken using natural light exclusively.

Table 5. Strong emotional responses to light type

Emotion	s_Angry		s_Disgust		s_Fear		s_Sad		s_Surprise		s_Happy		s_Neutral		n
artificial	0	0%	7	18%	7	18%	8	20%	5	13%	4	10%	3	8%	40
natural	5	25%	3	15%	2	10%	2	10%	3	15%	13	65%	8	40%	20
both	6	15%	7	18%	3	8%	8	20%	7	18%	4	10%	7	18%	40

The strong Happy reactions were detected with photos that used natural lighting. Photos with natural light also recorded numerous Neutral reactions. At the same time, no strong Angry reactions were registered for photos with artificial light. Photos with artificial lighting had the lowest results for both Happy and Neutral emotions.

Next, the brightness of the colour scheme was analyzed. To perform the brightness analysis, each image was converted to grayscale, and the shade of each pixel was examined, where 0 = black and 255 = white. The average value of all pixels was then calculated and converted into a percentage, where 0% represents pure black and 100% represents pure white. Photos that scored between 64% and 77% were classified as bright, those scoring between 49% and 63% were classified as medium, and those scoring between 34% and 48% were classified as dark.

Table 6. Strong emotional responses to brightness of color scheme

Emotion	s_Angry		s_Disgust		s_Fear		s_Sad		s_Surprise		s_Happy		s_Neutral		n
bright colors	2	5%	8	21%	5	13%	7	18%	7	18%	5	13%	8	21%	39
dark colors	2	4%	3	6%	1	2%	0	0%	6	12%	4	8%	1	2%	49
medium	7	58%	6	50%	6	50%	11	92%	2	17%	12	100%	9	75%	12

The highest number of strong Happy reactions was detected in photos where the brightness of the colour scheme was at a medium level. At the same time, a large group of these photos registered the presence of Sad (92%) or Neutral (75%) emotions. Dark-coloured photos rarely triggered emotional reactions (the lowest being 0% for Sad and the highest being 8% for Happy). Based on this, it can be concluded that dark photos evoke the fewest emotional reactions. Photos with medium brightness elicit the most reactions, but these reactions are often extreme (sometimes occurring simultaneously).

Photos with a warm colour tone were classified as those containing more warm tones, such as yellows, oranges, and browns. Photos with a cool colour tone were those dominated by whites, greys, and shades of blue. The analysis of colour tones was conducted three times by two experts and ChatGPT (using Python code to analyze).

Table 7. Strong emotional responses to color tone

Emotion	s_Angry		s_Disgust		s_Fear		s_Sad		s_Surprise		s_Happy		s_Neutral		n
warm colors	8	13%	8	13%	6	10%	10	16%	10	16%	16	25%	9	14%	63
cool colors	3	8%	9	24%	6	16%	8	22%	5	14%	5	14%	9	24%	37

Photos with a warm colour tone elicit the most positive reactions (25% of the photos triggered a strong Happy reaction). Among the reactions to photos with a cool tone, Disgust (24% of the photos) and Sad (22% of the photos) are predominant.

Another aspect analyzed in the photos was the presence of colour accents. Photos featuring subtle, pastel colours were classified as “subdued”, while those with distinct

colour accents (e.g., yellow, red, navy blue) were placed in the "distinct accents" category. These colours included accents such as pillows, curtains, or paintings. It was found that 61 photos depicted rooms with a subdued colour scheme, while 39 photos had distinct colour accents visible (n).

Table 8. Strong emotional responses to color accents

Emotion	s_Angry		s_Disgust		s_Fear		s_Sad		s_Surprise		s_Happy		s_Neutral		n
subdued	6	10%	9	15%	7	11%	12	20%	8	13%	9	15%	13	21%	61
distinct accents	5	13%	8	21%	5	13%	6	15%	7	18%	12	31%	5	13%	39

Photos with distinct colour accents elicited the most strong emotional reactions (31% of the photos triggered a strong reaction), and these were predominantly positive reactions: Happy. At the same time, as many as 21% of such photos elicited a Disgust reaction. Therefore, the specific colour used might play a significant role in triggering emotions. Photos with a subdued colour scheme more often provoked Neutral reactions (21% of the photos) or Sad reactions (20%).

Next, the presence of accessories in the photos, such as books, trays with food, glasses, decorative blankets, and others, was analyzed. It was found that accessories were present in 39 photos, while 61 photos did not contain any accessories (n).

Table 9. Strong emotional responses to presence of accessories

Emotion	s_Angry		s_Disgust		s_Fear		s_Sad		s_Surprise		s_Happy		s_Neutral		n
present	5	13%	5	13%	5	13%	8	21%	3	8%	10	26%	5	13%	39
absent	6	10%	12	20%	7	11%	10	16%	12	20%	11	18%	13	21%	61

Photos with visible accessories elicited the most reactions, primarily Happy reactions - 10 times (26% of the photos with accessories) and Sad reactions - 8 times (21%). For photos without visible accessories, 13 Neutral reactions were observed (21% of such photos), along with 12 Disgust and 12 Surprise (20% of such photos each).

It was also analyzed whether a window was visible in the photo. It was found that the majority of the photos showed a window, with 65 such photos in the dataset. There were 35 photos where no window was visible.

Table 10. Strong emotional responses to presence of the windows on the image

Emotion	s_Angry		s_Disgust		s_Fear		s_Sad		s_Surprise		s_Happy		s_Neutral		n
present	8	12%	9	14%	10	15%	14	22%	8	12%	13	20%	12	18%	65
absent	3	9%	8	23%	2	6%	4	11%	7	20%	8	23%	6	17%	35

Based on the collected data on the emotional reactions, it is difficult to determine whether the participants prefer a window to be visible in the photo. A noticeable difference can be seen with the Sad reaction, which occurred in response to 22% of photos with a visible window, while for photos without a visible window, the Sad reaction occurred in only 11% of such photos. There were also more Happy reactions for photos without a visible window than for those with a visible window. However, the absence of a window more frequently evoked emotions such as Surprise and Disgust.

The way participants reacted may depend on whether, besides the presence of a window in the photo, the view outside the window is discernible. This was the next aspect analyzed. In 13 photos, the view outside the window is visible, while in 30 photos, the

view is blurred. The group of photos without a view included both those without a window and those where the window was so brightly lit that it was impossible to determine what was outside.

Table 11. Strong emotional responses to presence of the view outside the window

Emotion	s_Angry		s_Disgust		s_Fear		s_Sad		s_Surprise		s_Happy		s_Neutral		n
visible	4	31%	0	0%	3	23%	6	46%	2	15%	3	23%	2	15%	13
not visible	4	7%	10	18%	7	12%	7	12%	12	21%	11	19%	12	21%	57
blurry	3	10%	7	23%	2	7%	5	17%	1	3%	7	23%	4	13%	30

Photos with a view outside the window primarily elicited strong emotional reactions in the areas of Sad (46%) and Angry (31%) among the participants. However, photos with a clear view (23%) or a blurred view (23%) slightly more often triggered a Happy reaction compared to photos without a view outside the window (19%).

Table 12. Strong emotional responses to the photo category

Emotion	s_Angry		s_Disgust		s_Fear		s_Sad		s_Surprise		s_Happy		s_Neutral		n
from the front	0	0%	0	0%	0	0%	1	10%	1	10%	3	30%	2	20%	10
from the side	1	5%	2	10%	3	15%	2	10%	2	10%	4	20%	1	5%	20
from behind	2	10%	1	5%	1	5%	2	10%	2	10%	2	10%	1	5%	20
in close-up	2	20%	4	40%	2	20%	0	0%	2	20%	2	20%	3	30%	10
with people	1	10%	1	10%	2	20%	1	10%	1	10%	2	20%	2	20%	10
angled, short shot	2	20%	4	40%	1	10%	5	50%	3	30%	2	20%	7	70%	10
angled, long shot	1	10%	3	30%	2	20%	6	60%	2	20%	4	40%	2	20%	10
other	2	20%	2	20%	1	10%	1	10%	2	20%	2	20%	0	0%	10

Photos taken at an angle, in a short shot, most frequently elicited a strong Neutral emotional reaction (70% of such photos triggered this reaction). Additionally, 50% of these photos triggered a Sad reaction. The Sad reaction was also observed among participants when viewing 60% of photos in the angled, long shot. However, these shots often generated positive emotions, with 40% of these photos eliciting a Happy reaction.

Similarly, 40% of photos in the close-up and angled, short-shot categories triggered a Disgust reaction. A Happy reaction was also elicited by 30% of photos taken from the front, while 30% of close-up photos triggered a Neutral reaction. Additionally, 30% of angled, short-shot photos elicited a Surprise reaction, and 30% of angled, long-shot photos triggered a Disgust reaction.

5 Discussion

In this study, the MorphCast Emotion AI HTML5 SDK tool was used to determine whether it is possible to apply a commercial Facial Expression Analysis tool to study consumer purchase preferences concerning photos of hotel rooms. It was found that conducting the study using the participant's laptop camera and a dedicated website allows for an almost cost-free implementation of such a study, even remotely. None of the participants expressed concerns or doubts about their participation. After explaining the principles of the experiment these individuals gave informed consent to have their emotions recorded using their own computer's camera and sent the console log file

(study results) to the researchers via email or messenger. According to information from the MorphCast tool's website, only 28% of people refuse to use their camera when the tool is installed on a website [70]. Therefore, it can be concluded that using this tool for research is quick and comfortable for participants (RQ1). It also does not require special equipment, unlike eye-tracking studies or heat maps.

According to research on hotel choice preferences, these vary depending on age and gender [71]. To eliminate uncertainties related to the influence of age and gender on preferences, the group was purposefully selected and consisted of 14 women aged 35-45. Despite this deliberate selection, participants' emotional reactions, and consequently their preferences regarding hotel rooms, varied significantly. It was also observed that some participants showed a clear dominance of a single emotion, which could have been due to their overall mood.

Photos of hotel rooms are among the most frequently used images in the presentation of travel offers [64]. As Expedia report points out [65], customers are keen to browse offers where the room is shown from various angles. However, when selecting photos for this study, it was found that certain shots are more popular than others. Hotels most commonly present rooms in angled shots (either close-up or from a distance) and much less frequently from the headboard side (from the back) or from the side.

Based on the results of this study, it was found that participants responded with positive emotions to photos with natural light, which aligns with the findings of Expedia [65] and Cuesta-Valiño et al. [69]. Participants also reacted more favourably to photos featuring warm colour tones, which supports the results obtained by Chi et al. [66]. However, Cuesta-Valiño et al. [69] claim that the type of light, its intensity (brightness), and the time of day depicted in the photo do not matter. Our findings indicate that photos with artificial lighting and dark photos more frequently triggered negative reactions. The most positive reactions were associated with photos of medium brightness, suggesting that cool colours, overly bright, or overexposed photos did not evoke positive emotional reactions.

Photos taken at an angle from a distance, showing the room in a wide perspective, elicited the most positive emotional reactions. Such photos make the rooms appear more spacious, and our results align with the findings of Cuesta-Valiño et al. [69].

As many as 8 out of 10 photos featuring people triggered strong emotional reactions, although there was no clear dominance of any particular emotional reaction. Cuesta-Valiño et al. [69] suggested that photos with people are generally perceived less favourably, except for those depicting hotel staff in uniforms. In the set of photos, there were two images showing hotel staff in uniform. One of these elicited a neutral reaction, while the other evoked sadness. Photos featuring people that generated emotion Happy depicted a couple on a terrace and a happy woman just after waking up.

Cuesta-Valiño et al. [69] argue that if there is a nice view outside a room's window, it should be shown in the photo. However, our study indicates that photos with a visible view outside the window often generate Sad or Angry emotions. Happy reactions occurred with similar frequency regardless of whether there was a view, no view, or a blurred view. Happy reactions were also more common for photos without any visible window compared to those where a window was visible. Positive reactions were also elicited by photos that featured accessories, such as food, or books, which is consistent

with the results of the mentioned study [69]. However, according to our results, better responses were obtained to photos with distinct colour accents, such as colourful pillows or curtains in bold colours, than to photos with subdued colours [69].

However, it can be stated that our findings are generally consistent with those obtained by other researchers using different methods. Considering this, along with the ease of use of the tool, its low cost, and the comfort for participants, it was concluded that the research question RQ1 can be answered affirmatively. This questions was regarding whether this method is suitable for identifying photos that evoke positive emotions in respondents. It was also found that common elements can be identified in photos that evoke positive emotions (RQ2). Highlighting the features of photos that generated most Happy reactions, it can be stated that these are photos with natural lighting, medium brightness of colours, warm colour tones, and the addition of distinct colour accents. The presence of a window and the view outside the window were not decisive factors in this case. The photo should be taken at an angle (long shot), or from the front.

6 Conclusion

Emotion analysis is crucial for understanding how an advertisement or product affects its audience. Utilizing tools that enable the analysis of large datasets, including extensive data on emotions, helps predict consumer behaviour and supports marketing staff and photographers. With the information gathered from such analysis, they can highlight specific features of hotel rooms to enhance customer satisfaction. This also positively impacts the efficiency of marketing efforts and reduces costs. Managers do not need to commission a large number of photos, including those that may be less well-received by customers, nor do they need to publish an excessive number of photos. As Bufquin [68] points out, an excessive number of images can complicate website navigation and distract consumers from making a reservation.

Among the limitations of this study, first to note is the variability in the facial expressions of the participants. Although the software was designed to detect micro-expressions, it should be clearly stated that the results showed significant outliers—some participants recorded zero values for selected emotions throughout the entire study. The participants' current emotional state and attitude could have significantly influenced the results. In the future, the study could be expanded to include in-depth interviews with the respondents. The second limitation of this study is the limited sample. The study was conducted on a small, purposefully selected sample of 14 people. Conducting the study with a larger number of respondents, as well as comparing the results with those from another sample (e.g., men), could provide a broader perspective on which photos are preferred. Additionally, the study was conducted exclusively among respondents in Poland. Individuals from other countries might demonstrate different preferences due to differences in upbringing, culture, and perceptions of aesthetics. The tool used for the study did not always function correctly. Two console log files were discarded, and the corresponding respondents were not included in the study. Some respondents agreed to repeat the study after a technical issue was identified. The fact that they viewed the photos more than once may have affected their emotional reactions to the images.

Despite the limitations mentioned, we believe that the method described in this study is suitable for researching recognizing emotional reactions. This provides a methodological contribution to marketing research. Furthermore, the study identified the type of photos preferred by women aged 35-45, which could have significant implications for managers. Further research should continue with different respondent groups and focus on photos depicting other parts of the hotel. This method could also be used for studying product photos for e-commerce.

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