

## Research Article

## Leveraging AI and social media for actionable insights for nature park management

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## ABSTRACT

Natural Park management can benefit from the vast number of visitors' posts on social media platforms. In this research, we collected posts related to the Ramat Hanadiv Nature Park in Israel from 13 social media platforms. We analyzed texts and photographs using artificial intelligence (AI)-based methods, including the OpenAI functions in Atlas.ti, ChatGPT, and Google Cloud Vision. Regarding texts, we investigated visitors' positive and negative emotions based on Plutchik's wheel of emotions. For photographs, we investigated visitors' interests according to different demographics such as provenance, language, and gender. Throughout the research, we worked collaboratively with the park management team in an iterative process. Most of the textual data reflected positive feedback about the park, although practitioners found negative feedback and emotions and visitor demographics particularly new and useful. Overall, the use of AI greatly increases the variety of themes, preferences, and emotions that can be investigated. Practitioners saw great potential in the approach to support Nature Park planning and management.

## 1. Introduction

Adequately characterizing the perceptions and opinions of tourists and local visitors is essential for effective management of nature parks and protected areas (Bhatt & Pickering, 2021; Perera et al., 2015). Natural areas provide a broad range of complex and often intangible ecosystem services to people (Depietri et al., 2016; Langemeyer et al., 2015). However, managing parks and gardens to enhance the depth and meaningfulness of the visitors' experience, while balancing potentially conflicting goals, such as conservation of biodiversity, ecological value, or heritage preservation, can be challenging (Candrea & Ispas, 2009).

Passive crowdsourcing of social media data and other user-generated content has emerged as a novel tool to characterize behavior and interactions of park visitors with the natural and cultural environment (Depietri et al., 2023; Pickering et al., 2023). In the context of this rapidly growing literature (Ghermandi et al., 2023), several studies have focused on assessing the environmental and cultural values of green and blue areas (Angradi et al., 2018; Bernetti et al., 2019; Calcagni et al., 2019). Others have specifically assessed visitor perceptions about

natural parks (Bhatt & Pickering, 2021; Kim et al., 2019), preferences (Ghermandi, Camacho-Valdez, & Trejo-Espinosa, 2020; Huai & Van de Voorde, 2022; Song et al., 2022), and economic values of nature-based recreation (Sinclair et al., 2020). Information from social media data can complement that derived from more conventional methods based on interviews, surveys, participant observation, and focus group discussions (Depietri et al., 2021; Gkoltsiou & Paraskevopoulou, 2021).

A growing area of interest lies in analyzing social media data to characterize visitors' emotions and preferences. Traditionally, capturing the emotional responses of visitors to their experiences of a park has been challenging and resource intensive. Qualitative methods, depending on interacting with users or users' self-reports after the visit (Brown & Fagerholm, 2015), are difficult as emotions and their recollection get easily distorted or lost over time (Park et al., 2020). These studies also tend to have limited spatial and temporal coverage due to the small sample sizes involved (Luhmann, 2017). Mobile technologies, including portable sensors and wearable devices, such as smartwatches or fitness trackers (Luhmann, 2017), or walking interviews (Teff-Seker & Orenstein, 2019) allow to collect detailed data from travelers in real time and

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in real-world settings (Benita et al., 2019). However, these methods, too, are characterized by weaknesses described above – small sample sizes, subjective interpretations, and heavily influenced by temporal and spatial specificity.

User-generated content from social media offers new opportunities to study emotions and interests while circumventing some of the limitations of self-reporting by users (Luhmann, 2017). The large sample size, limited facilitator bias and the collection of information in quasi-real time are advantages of this approach (Kong et al., 2022; Luhmann, 2017). Tags, hashtags, emoticons, and emojis, for instance, often directly convey emotions and perceptions (Roberts et al., 2018; Weaver et al., 2021; Wu et al., 2020) and have been found to correlate with emotional and subjective well-being at the time of the visit (Jaidka et al., 2020; Settanni & Marengo, 2015). Social media users generally frankly and passionately share their stories, although emotional contagion and the prevalence of polarized views in social media also need to be considered (Ferrara & Yang, 2015; Papworth et al., 2015).

The analysis of visitors' emotions and interests through the analysis of social media data has great potential to provide actionable insights into park management. Previous research focused, for instance, on geographical distribution problems of green areas, prioritization of financial investments in parks, park usage characteristics, and users' preferences of park attributes (Huang et al., 2022). Other studies have focused on landscape and nature appreciation, on the characterization of recreational activities, and on detecting interest in, and affective ties to, historical monuments in parks (Mouttaki et al., 2022; Song & Zhang, 2020). Song and Schuett (2023) analyzed the links between social motivation in posting to social media and place dependence, place identity, and place affect. Still other researchers have attempted to analyze visitors' emotions to enhance the social value of nature parks and to build political support to justify the existence of these spaces (Hausmann et al., 2020). Human emotions and human demands are also analyzed to identify the preferences for different landscape features and to improve urban greenspace planning (Chen et al., 2022; Plunz et al., 2019). This type of work focuses as well on the analysis of negative opinions or experiences associated with communing in nature (Niezgoda & Nowacki, 2020). Finally, Mangachena and Pickering (2021) analyzed public views and sentiments regarding specific park management topics.

Recent technological developments in artificial intelligence (AI) technologies can assist researchers in extracting valuable information from social media data. Broadly speaking, AI is the “ability of machines to mimic human thinking, learning, reasoning, planning, communication, and decision making” (Dauvergne, 2020, p. XII). As such, AI helps to understand complex situations by integrating qualitative and quantitative data thus facilitating or imitating human-like tasks (Schoormann et al., 2023). Machine Learning (ML), the prevailing algorithmic approach within AI (Schoormann et al., 2023), consists of a branch of computational algorithms designed to emulate human intelligence through learning processes (El Naqa & Murphy, 2015). ML is the primary method used for developing practical software for computer vision, speech recognition, natural language processing (NLP) and other applications (Jordan & Mitchell, 2015).

AI promises to play a pivotal role in revealing insights that are otherwise hidden in large amounts of unstructured data, such as social media photos and texts (Nishant et al., 2020). Several studies have made use of AI tools in support of natural resources management. These notably include the analysis of photographs through computer vision to characterize visitors' interests and preferences (Ghermandi et al., 2022; Lee & Son, 2023; Song et al., 2022; Staab et al., 2021; Väisänen et al., 2021), and the analysis of texts through sentiment analysis to broadly detect levels of satisfaction (i.e., positive, neutral, or negative) associated with visitors' experiences (Brindley et al., 2019; Cao et al., 2022; Chen et al., 2022; Do, 2019; Huai & Van de Voorde, 2022; Kong et al., 2022; Plunz et al., 2019). Only a limited number of studies combine insights from both visual and textual analysis (Zhao et al., 2024).

While visual analysis of photographs through commercial computer

**Table 1**

AI tools to analyze or code texts from social media data with application to natural parks and their visitors' emotions.

AI tool	Emotion categories	Case study	Reference
'nrc' emotion lexicon of 'Syuzhet' package in R	Anger, fear, anticipation, trust, surprise, sadness, joy, disgust	Selected national parks in South Africa	Mangachena and Pickering (2021)
'nrc' emotion lexicon of 'Syuzhet' package in R	Anger, fear, anticipation, trust, surprise, sadness, joy, disgust	Selected national parks in South Africa	Hausmann et al. (2020)
Transformers-BERT model and GoEmotions dataset	Joy, neutral, sadness, fear, surprise, anger, disgust	East Coast Park in Singapore	Yang and Zhang (2024)
Deep learning (BERT and BiLSTM models)	Excited, joy, respect, satisfaction, surprise, tired, regret, complain, sadness, fear	Tourist attractions in Nanjing, China (incl. urban green spaces)	Ruan et al. (2022)
BERT model	Happiness, anger, sadness, fear, surprise, neutral	Wuhan, China (incl. urban green spaces)	Wang et al. (2023)

vision tools such as Google Cloud Vision and Clarifai (Ghermandi, Sinclair, et al., 2020; Lee et al., 2019) or through facial expression recognition software (Do, 2019; Huang et al., 2022; Li et al., 2022; Zhu et al., 2021) can, to some degree, assist in identifying human emotions expressed in photographs, there is a still largely unexplored potential for text-based AI tools. To date most analyses of social media data through AI in support of natural resources management has made use of computer vision (Ghermandi et al., 2022; Lee & Son, 2023; Song et al., 2022; Staab et al., 2021; Väisänen et al., 2021), while far fewer studies have utilized AI to conduct textual analysis in this field (see Table 1).

The recent developments in the use of social media textual data suggest that AI tools can greatly improve our capacity to assess the emotions of visitors to natural areas (Huai & Van de Voorde, 2022; Mouttaki et al., 2022). Table 1 lists studies making use of various AI methods to extract information about emotions from texts uploaded to social media platforms, specifically focusing on urban or natural park visitation and management. These studies implement text mining, an interdisciplinary field which draws on information retrieval, ML, statistics, and computational linguistics (Sergiacomi et al., 2022). They generally rely on emotion lexicons, which are either pre-existing – such as Canada's National Research Council (NRC) (Hausmann et al., 2020; Mangachena & Pickering, 2021) and the GoEmotions lexicons (Yang & Zhang, 2024) – or are specifically developed for a particular case study (Garzia et al., 2022). They may include advanced deep learning language models such as Bidirectional Encoder Representations from Transformers (BERT) (Ruan et al., 2022; Wang et al., 2023) to assess a wide range of positive and negative visitor emotions, such as anger, fear, anticipation, trust, surprise, sadness, joy, and disgust.

The advent of Generative AI Large Language Models (GLLMs) such as OpenAI's ChatGPT chatbot (Juliante et al., 2023) promises to enhance the speed and accuracy with which large amounts of textual data, including from social media tags and comments, can be analyzed. Coding thousands of textual data can be done in a matter of hours with the potential to improve transparency in the coding (Siiman et al., 2023). GLLMs can also increase the array and flexibility in the types of cultural ecosystem services, visitors' interests and emotions that can be analyzed. Initial studies on the coding of qualitative data through OpenAI technologies have given good results when compared to manual analysis on the same datasets (Morgan, 2023). To the best of our knowledge, however, studies have yet to make use of the OpenAI applied to social media textual data to identify visitors' emotions for supporting natural park management. This study is thus one of the first

to investigate the promising potential for applying ChatGPT to this use.

The present study aims to demonstrate how actionable insights for park management and park renovation can be derived from the analysis of social media texts and photographs through the application of state-of-the-art AI techniques. We also adopted a coordinated framework for two-way communication and evaluation between researchers and park managers. In other words, we adopt a transdisciplinary, socio-ecological approach (Holzer et al., 2018) in which the research questions are developed in coordination with the park managers (such as the focus on exploring positive and negative emotions of park visitors). The initial analyses and their refinement are also conducted iteratively in consultation with park managers, and the results and their meanings and implications are discussed collaboratively between the researchers and the practitioners. In doing so, we develop an innovative approach to the application of AI tools for emotional analysis of user-generated texts by examining the potential of recently developed GLLMs, such as ChatGPT, and immediately exploit the opportunity for its applied value. The case-study application is the popular Ramat Hanadiv Nature Park and Memorial Garden in Israel. More specifically the study aims to:

1. Explore the potential of novel AI tools, including those based on GLLMs, for the analysis of emotions expressed in user-generated social media texts posted by park visitors, to support management purposes.
2. Combine information about the content of social media photographs derived from computer vision with socio-demographic user information to characterize the interests of different segments of the population of park visitors.
3. Assess the potential application of the results obtained with these methods in collaboration with park managers.

In pursuing these objectives, the study addresses several research gaps. First, it greatly extends the pool of investigated social media sources compared to previous studies. Second, it provides an assessment of the usefulness, novelty, and perceived validity of the study's findings through the analysis of the responses to an evaluation questionnaire, which was distributed among Ramat Hanadiv Nature Park managers as the final stage of the research. Third, it considers and elaborates upon the benefits derived from the application of advanced AI technologies

for the analysis of large datasets containing textual data. Finally, the results of the study provide guidance for future researchers who wish to explore and navigate through diverse types of information that can be extracted from social media data analysis, to catalyze discussion and formulate empirically based management strategies for protected areas.

## 2. Methodology

### 2.1. Case study

This research was conducted at the Ramat Hanadiv Nature Park, which is found at the southern tip of Mount Carmel on Israel's northern Mediterranean coast (32°32'37" N 34°56'37" E; see Fig. 1). The Nature Park is privately owned and surrounds the Memorial Gardens for Baron Edmond de Rothschild. It is operated and managed by the Rothschild Foundation for the welfare and use of the public. The site covers about 500 ha and is bordered by urban areas, intensive agriculture, road infrastructure, and a railway.

In the heart of the park are cultivated, European-style Memorial Gardens, surrounding the tomb of the Baron and his wife Ada, and a visitor pavilion. The Nature Park and Memorial Gardens attract around, on average,  $650,000 \pm 33,000$  annual visitors to the nature park during 2013–2019, with an average annual visitation growth rate of  $6\% \pm 3\%$  according to Zukerman et al. (2024).

The Nature Park consists of a diverse landscape mosaic that combines natural landscapes, planted coniferous groves, and traditional agriculture, and supports a rich and unique diversity of local flora and fauna (Koniak et al., 2011; Perevolotsky, 2013). Historical and archaeological sites from different periods have been restored and are accessible through a system of walking and cycling trails.

In 2023–24, a strategic process designed to outline the future development directions of the site was initiated, guided by the vision of "reconnecting humans with nature" (co-author LH, personal experience). The new strategic plan of Ramat Hanadiv aims at contributing to reversing the gradual and continuous disconnection between humans and their natural environment (i.e., the extinction of experience), which negatively affects physical, cognitive and mental health of people. The present research actively aims at supporting the next step in the implementation of the plan, not least by identifying what elements of the

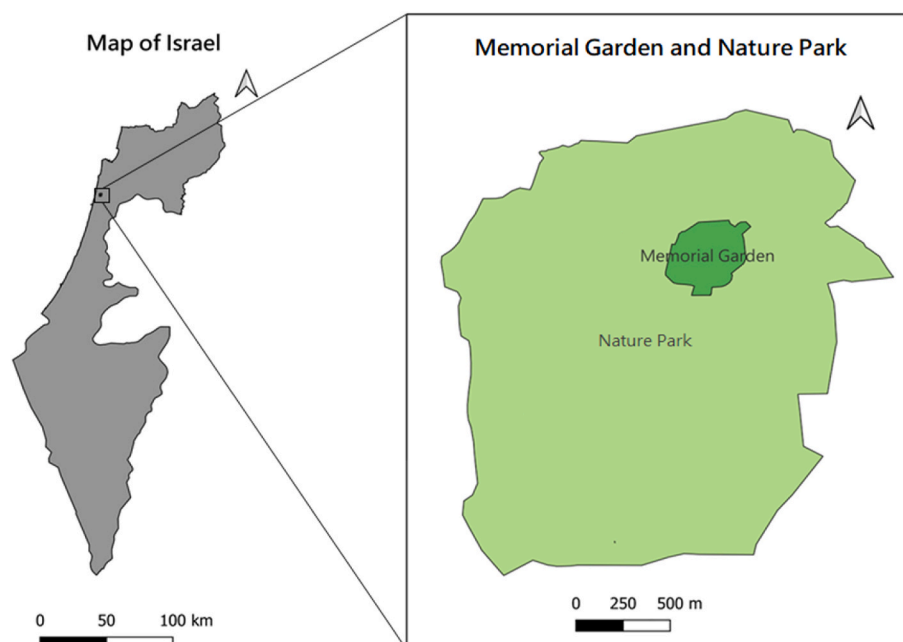


Fig. 1. Location and map of the Ramat Hanadiv nature park and memorial garden.

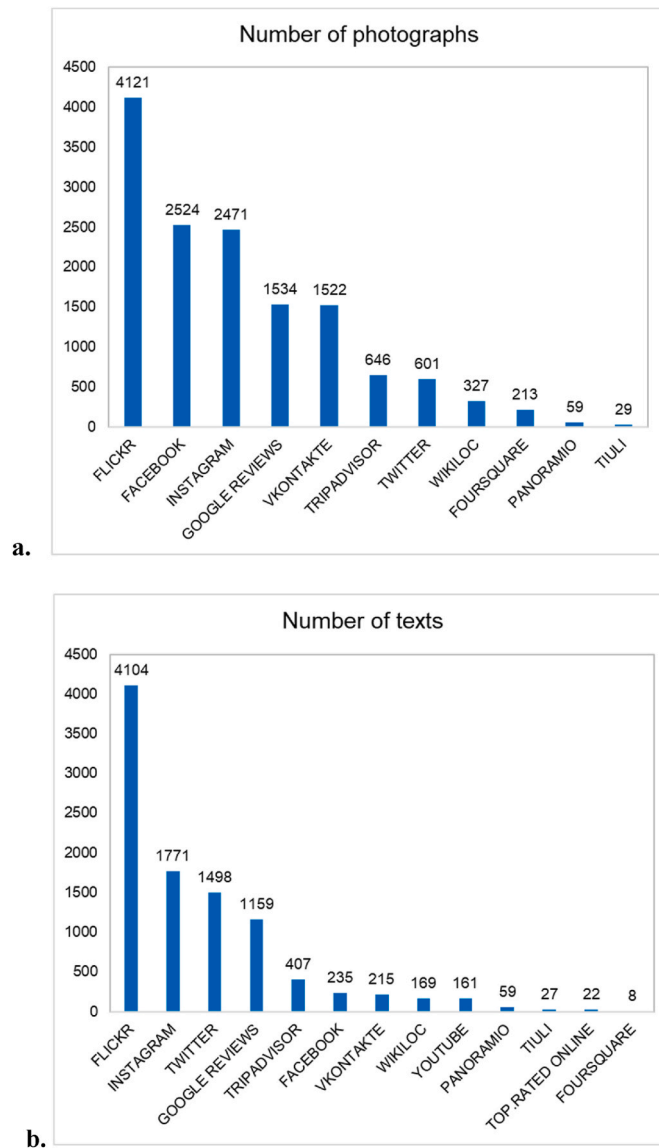


Fig. 2. a. and b. Number of photographs collected per social network platform (a) and number of texts collected per platform (b).

landscape trigger the most interest and appreciation in people.

## 2.2. Data collection

We collected social media data related to Ramat Hanadiv in the form of photographs and texts from 11 and 13 different platforms, respectively (Fig. 2a and 2b). We retrieved all the available data from the establishment of the platforms until the end of 2022 (starting year of the research study), except for Facebook, Instagram, Google Reviews (for which we retrieved only 2021/2022), and Panoramio (for which we only have data until 2014). Most of the photographs were collected from Flickr, Facebook, and Instagram, while texts were mostly collected from Flickr, Instagram, and Twitter (now X). Some of the photographs had texts associated with them, while others did not, and vice versa. The data retrieval process was performed differently for each platform and in accordance with their respective Terms of Service. It also involved manual data collection for platforms that do not allow automated retrieval of the data, or reliance on the platforms' Application Programming Interfaces (APIs). Additional details about data collection for each of the platforms are provided in Supplementary Material A.

Where possible, we extracted demographic information about the

home (community/city/region) location and gender of individual users from their public user profile. We further relied on the profile photograph and/or the user's first name, where available, to derive information on the gender, when this was not explicitly reported in the profile. This is consistent with the techniques implemented in previous studies (Calcagni et al., 2023; Hamstead et al., 2018; Martinez-Harms et al., 2018). The probability of a first name being male or female in Israel was estimated from Gender API (<https://gender-api.com>; accessed September 2023). We used a 95 % threshold on the probability of a first name being associated with a specific gender to minimize the potential for misclassification. When the gender assigned based on profile picture and first name did not match, we relied on the profile picture. To note is that this could lead to a small amount of misidentification based on subjective judgment.

Based on the home location in the profiles, users were divided between international tourists and domestic visitors. Domestic visitors were further classified into nine sub-groups, which included "local" visitors (the three towns in immediate proximity of the park), "regional" visitors (23 communities within a range of ~5–15 km of the park), and visitors coming from one of the seven districts designated by the Central Bureau of Statistics (<https://www.cbs.gov.il>). The list of localities pertaining to the categories of local and regional visitors is provided in Supplementary Material B and was agreed upon with the managers of the park. Finally, we further classified users based on the language of their texts, as identified by the "detectlanguage" function in Google Sheets (<https://support.google.com/docs/answer/3093278>).

## 2.3. Analysis of the texts

We collected a total of 9835 texts from the 13 social network platforms (Fig. 2b). Texts were coded with the Atlas.ti AI coding function (beta version), which is driven by ChatGPT's model from OpenAI. This produced 1256 codes and 19,670 quotations. We then grouped, through an iterative process amongst three authors of this paper, the 1256 codes in 30 groups (see Supplementary Material C). Some of the AI codes pertain to more than one group. We considered for further analysis and

Table 2

Groups of codes for positive emotions with number of quotations and codes per group.

Positive emotions – groups of codes	Code examples	Quotations per group	Codes per group
Love	Appreciation; appreciation of nature; nature appreciation	797	42
Amazement	Appreciation of nature; beauty; awe	709	54
Admiration	Appreciation; nature appreciation; gratitude	624	68
Acceptance	Self-acceptance; cultural diversity; cultural appreciation	504	16
Joy	Enjoyment; happiness; positive emotion	410	38
Serenity	Satisfaction; comfort; contentment	97	27
Interest	Interest; positive attitude; historical interest	88	36
Optimism	Positive attitude; optimism; encouragement	58	22
Anticipation	Enthusiasm; motivation; personal growth	49	16
Surprise	Awe; adventure; surprise	36	6
Trust	Encouragement; community engagement; friendliness	30	19
Vigilance	Exploration; nature exploration; perseverance	13	6
Ecstasy	Success; nature scenery; scenery	11	7
Total		3426	357



**Table 3**  
Groups of codes for negative emotions with number of quotations and codes per group.

Negative emotions – groups of codes	Code examples	Quotations per group	Codes per group
Disapproval	Disappointment; frustration; negative experience	131	67
Annoyance	Restrictions; ambivalence; difficulty	23	18
Pensiveness	Nostalgia; reminiscence; self-awareness	22	10
Apprehension	Confusion; uncertainty; ambivalence	21	9
Fear	Fear; environmental concern; safety	19	11
Boredom	Confusion; boredom; fatigue	10	4
Disgust	Betrayal; denial; envy	5	5
Anger	Anger	3	1
Loathing	Cold weather; cynicism; desertion	3	3
Grief	Grief; homesickness	2	2
Sadness	Rejection; unhappiness	2	2
Aggressiveness	Aggressiveness	1	1
Contempt	Objectification	1	1
Remorse	Regret	1	1
Total		244	135

elaboration of the data only three groups: positive emotions (with 1027 quotations and 202 codes); negative emotions (with 137 quotations and 119 codes); and flora (with 90 quotations and 36 codes) as an example. By manually regrouping and adding other relevant codes related to positive and negative emotions we obtained 3426 quotations and 357 different codes for positive emotions and 244 quotations (see Table 2) and 135 codes for negative emotions (see Table 3). Positive emotions represent about 93.3 % of all quotations related to emotions.

Specifically, we regrouped the codes of positive and negative emotions into subgroups of emotions according to the categories identified in Plutchik’s wheel of emotions (Plutchik, 2001) (Tables 2 and 3). Plutchik’s wheel consists of eight sectors of primary emotions (joy, anger, disgust, anticipation, sadness, fear, trust, and surprise), which are

**Table 4**  
Elements identified by the ChatGPT analysis of the Atlas.ti quotations report for the positive emotion “Love”.

Example of positive emotion: LOVE	Quotations: 797 (21.7 % of all quotations for emotions)
<b>Query:</b> From all the texts added please list the ten things in park or in the garden that trigger a feeling of love.	
<b>Output:</b> Based on the texts provided, here are ten things in Ramat Hanadiv Park or the gardens that trigger a feeling of love: <b>1. Beautifully tended gardens:</b> love for nature and its beauty. <b>2. Flowers:</b> creating a romantic and lovely atmosphere. <b>3. Peace and tranquility:</b> sense of love and serenity. <b>4. Scenic views:</b> inspire feelings of love and awe. <b>5. Fountains:</b> add a touch of elegance and charm to the park, creating a romantic ambiance. <b>6. Romantic strolls:</b> The park’s pathways provide an opportunity for couples to take leisurely walks together, enjoying each other’s company and the beauty of the surroundings. <b>7. Romantic seating areas:</b> The park offers seating areas where couples can sit, relax, and enjoy intimate moments surrounded by nature. <b>8. Wedding photos:</b> The park is mentioned as a location for wedding photos, indicating that it holds a romantic appeal for couples celebrating their love. <b>9. Charming atmosphere:</b> The overall ambiance of the park, described as lovely, magical, and relaxing. <b>10. Love for history and heritage:</b> The park’s connection to the history and legacy of Baron Rothschild, can evoke a sense of appreciation and love for the past. These elements combined create an environment that triggers feelings of love and appreciation for nature, beauty, history, and each other.	

**Table 5**  
Elements identified by the ChatGPT analysis of the Atlas.ti quotations report for the negative emotion “Disapproval”.

Example of negative emotion: DISAPPROVAL	Quotations: 131 (3.5 % of all quotations for emotions)
<b>Query:</b> From the two texts uploaded could you please list the major causes of disapproval?	
<b>Output:</b> Based on the two texts provided, the main causes of disapproval regarding Ramat Hanadiv can be summarized as follows: <b>1. Negative Customer Service:</b> Many comments express dissatisfaction with the customer service and interactions with staff members at Ramat Hanadiv. Visitors mention encounters with impolite, aggressive, or unhelpful staff, which negatively impacted their experience. <b>2. Lack of Accommodation for Children and Families:</b> Some visitors express disapproval of the park’s policies and restrictions that do not accommodate families with young children. This includes limitations on children playing on the grass, lack of suitable facilities, and overall unfriendliness towards families with children. <b>3. Changes in Entrance Fees:</b> The introduction of entrance fees or parking fees is mentioned as a cause of disapproval. Visitors express disappointment with the shift from free entry to paid access, particularly when the park was previously accessible without charge. <b>4. Maintenance and Quality Decline:</b> The perceived decline in maintenance, lack of cleanliness, and deterioration of the park’s overall quality are mentioned as sources of disapproval. Visitors express disappointment with the neglected appearance of the gardens, lack of flowers, and general untidiness. <b>5. Lack of Dog-Friendly Policies:</b> Some visitors disapprove of the park’s policy that restricts dogs from entering the gardens. Dog owners express frustration with this policy, as they feel their pets should be allowed to accompany them during their visit. It’s important to note that these causes of disapproval are based on the specific comments provided and may not represent the overall sentiment of all visitors to Ramat Hanadiv.	

defined and arranged in four pairs of opposites, and multiple subgroups. Plutchik’s wheel of emotions is used in other studies to assess the range of emotions expressed in social media posts (Baudier et al., 2023; Kumar & Vardhan, 2022; Kušen et al., 2019; Tromp & Pechenizkiy, 2015; Weismayer et al., 2021).

We created reports of the quotations generated with Atlas.ti for the subcategories of positive and negative emotions listed in Tables 2 and 3. The reports were created using the function of Atlas.ti “Export as report”. We then uploaded the content of the reports to ChatGPT for the elaboration of the data. We created a chat in ChatGPT per emotion and we made queries regarding the uploaded text. The queries for each emotion are presented in Tables 4 and 5 in the results section and in Supplementary Material D for the remaining positive and negative emotions.

2.4. Analysis of the photographs

The dataset of 14,047 photographs underwent annotation using the Google Cloud Vision ML tool. This facilitated the association of each photograph with a maximum of 20 machine-generated tags, which provide a descriptive account of its visual content. This annotation process resulted in the compilation of a database of 272,289 individual tags, 2884 of which were unique tags. These tags were systematically classified into distinct aspects of nature-based recreation, adhering to the framework proposed by Egorova (2021) and later implemented by Ghermandi et al. (2022). This classification framework recognizes three overarching domains pertinent to nature-based recreation, namely: activity, environment, and emotions/cognition. Each of these domains is further subdivided into 28 aspects. Leveraging the lexicon established by Ghermandi et al. (2022), we expanded it to incorporate novel tags generated through the present analysis. Moreover, we extended the taxonomy concerning the aspect “wildlife and vegetation”, introducing a fourth-tier classification to distinguish domestic animals, wild animals, flowering plants, trees, and other biological entities. The latter also included ambiguous tags like “animal” or “annual plant” that defy

unequivocal assignment to any of the preceding categories. A schematic representation of the hierarchical structure of the classification framework is shown in Fig. E1 in Supplementary Material E.

We further characterized the specific interests that each group of visitors (see Fig. 4) manifested through the photographs they shared online based on the most representative tags. To identify the most representative tags or nature-based recreation aspects within each group of users we relied on both (1) the absolute frequency with which the tags appear, and (2) the Term Frequency-Inverse Document Frequency (TF-IDF) coefficient of each individual tag. The TF-IDF technique (Landauer et al., 1998) is often used in text data mining and information retrieval to identify the words that best characterize a text within a collection of texts. The score considers both the number of times the word appears in a specific text (TF) and the rarity of such word among all considered texts (IDF). Thanks to the IDF correction factor, this procedure avoids selecting tags that are very common across all groups of users and thus not useful for differentiating between potential interests that are unique to specific user groups.

## 2.5. Practitioners survey and feedback

To assess the novelty, helpfulness, and validity of our results, we constructed a survey of 24 questions which we submitted to the professional staff of the Ramat Hanadiv Nature Park (including acting research director, scientific staff, educational staff). The questionnaire was constructed around a selection of statements derived from the analysis of the texts (10 questions), the metadata, and the photographs (10 questions). Regarding these statements, respondents were asked to assess newness, their helpfulness, and validity on a Likert scale from 1 (not at all) to 7 (very much), with 4 being neutral. Additional open questions were asked regarding a summary text elaborated in ChatGPT based on our input of quotations related to the category of flora. Here too, respondents were queried regarding the accuracy of the text, mistakes, new ideas and insights, and potential helpfulness of the information for the practitioners in their daily work. In total seven responses were collected, of which five were complete. One of the remaining two respondents completed about half of the survey while the second replied

only to the first two questions. Fig. 3 depicts how the responses from the practitioner survey were interpreted regarding the novelty, helpfulness, and validity of the information derived from our analysis.

Additional feedback was collected via interviews with park staff members at Ramat Hanadiv in charge of visitors, marketing, and education in the park. This feedback is also related to the usefulness and applicability of the research results for park management.

## 3. Results

### 3.1. Descriptive statistics

According to the analysis, about two thirds of the users investigated were domestic visitors (Fig. 4a). A breakdown of domestic visitors into regions or districts of provenance (Fig. 4b) indicates that most domestic visitors originated from Tel Aviv and Haifa districts. Notably, about 10 % of the visitors were locals, with an additional 6.4 % of visitors coming from the broader region surrounding the park. Male and female users appear to be equally represented in the sample of social media users (Fig. 4c), when assessed across all platforms. Hebrew and English are the languages in which most of the downloaded texts were written, with Arabic texts representing only 1.4 % of the sample (Fig. 4d). The temporal distribution of the data in Fig. 6 shows that, when averaged over all available years (see the methodology section), visits concentrated in the spring and autumn and that the daily peak of visit occurred between 9 a.m. and 11 a.m. To avoid double counting multiple posts by one single user during a single visit, we documented temporal distribution of user-days, i.e., unique combinations of user ID and date (Fig. 5a).

### 3.2. Analysis of the emotions expressed in the texts

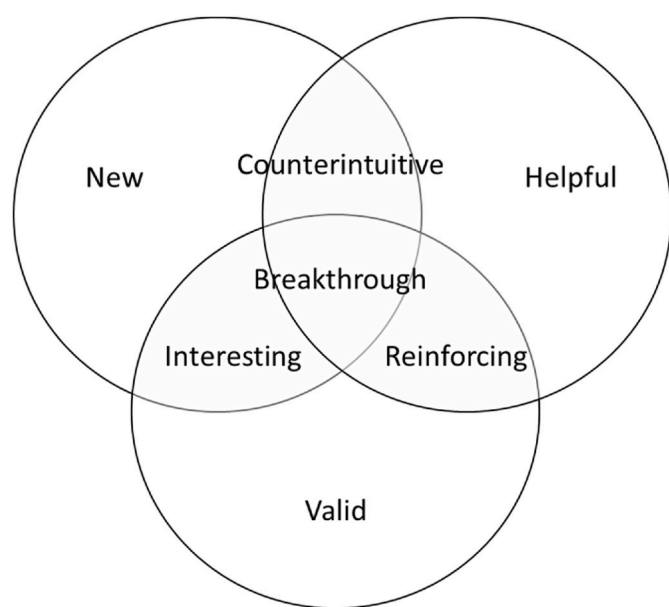
Regarding the analysis of the emotions, positive emotions were expressed far more than negative emotions. We recorded 3426 quotations reflecting positive emotions and 244 quotations only expressing negative emotions. The specific elements that were identified as reflecting each positive and negative emotion by ChatGPT are presented in Supplementary Material D and Tables 4 and 5. In this section we focus only on the elements signaling the most frequent positive emotion, love (with 979 quotations; Table 4), and the most frequent negative emotion, disapproval (with 131 quotations; Table 5).

The most frequent elements identified as reflecting love were the well-tended gardens, the flora, and the overall romantic atmosphere of the garden. Love was also expressed in the appreciation of the history and legacy of Baron Rothschild. While negative experiences related to the emotion disapproval were connected to dissatisfaction with park customer service, a perceived lack of infrastructure and services for families and children, introduction of entrance fees, a perceived decline in the maintenance of garden and park, and unfriendly dog-policies.

Amongst the broad categories of groups of additional groups of codes listed in Supplementary Material C, we selected the group “Flora” as potentially grouping elements of the landscape of major interest for visitors. From the report of the quotations under “Flora” built with Atlas.ti, we requested of ChatGPT to provide three possible elaborations of the information provided about flora, including 1) a summary of 300 words; 2) the list of species of flora that are mentioned by the visitors; 3) and the list of the types of gardens in which the Ramat Hanadiv is subdivided (Table 6). It is important to note that, according to park managers, some of the plants listed in Table 6, such as beach lilies, rosaria and flowers of lily, do not represent species or are species that do not grow in the garden. This might be due to erroneous geolocation or tagging or to translation errors.

### 3.3. Analysis of visitors' interests from photographs

The machine-generated tags that were most frequently associated with photographs for each aspect of nature-based recreation are



**Fig. 3.** Framework for analysis of the results from the practitioner survey. The three circles in the figure represent the three categories of novelty, helpfulness, and validity with which the respondents were asked to judge the selection of results in the survey. We also labelled the interpolation of these categories to characterize how respondents processed information in the respective overlapping categories.



**Fig. 4.** Estimated provenance of the investigated social media users: (a) international vs. domestic visitors and (b) in geographic origins of domestic visitors. Gender representation in sample (c) and proportional representation of language of posts (d).

presented in Supplementary Material F. Most photographs included visual elements that were related to nature-based recreation, to vegetation (e.g., “plants”, “grass”, “tree”, “flower”) and physical environment (e.g., “landscape”, “sky”, “natural landscape”). Among activities and social relationships, “leisure” activities and the presence of “people in nature” were most frequently identified, especially in a family context (“toddler”, “child”). “Fun” and “happy” were the feelings most often associated with the photographs.

While a breakdown of the machine tags by gender, language, and provenance of the users broadly confirms that these are the most frequently observed tags for all the groups of users, notable differences across groups emerge when analyzed with the TF-IDF technique, which emphasizes the uniqueness of a term that may be lost in simple frequency counts. Fig. 6 shows the machine tags with the highest TF-IDF score for the nine regions of provenance of domestic users. Tags in Fig. 6 are color-coded according to the aspect of recreation they reflect, if any. Similar figures are provided in Supplementary Material F divided according to gender, language, and international or domestic visitor groups.

Fig. 6 shows that machine tags related to recreational activities and activity-related artifacts, especially pertaining to biking, better characterize regional visitors and, to a lesser extent, visitors from Haifa and Tel Aviv districts, compared to the other groups. A greater importance for

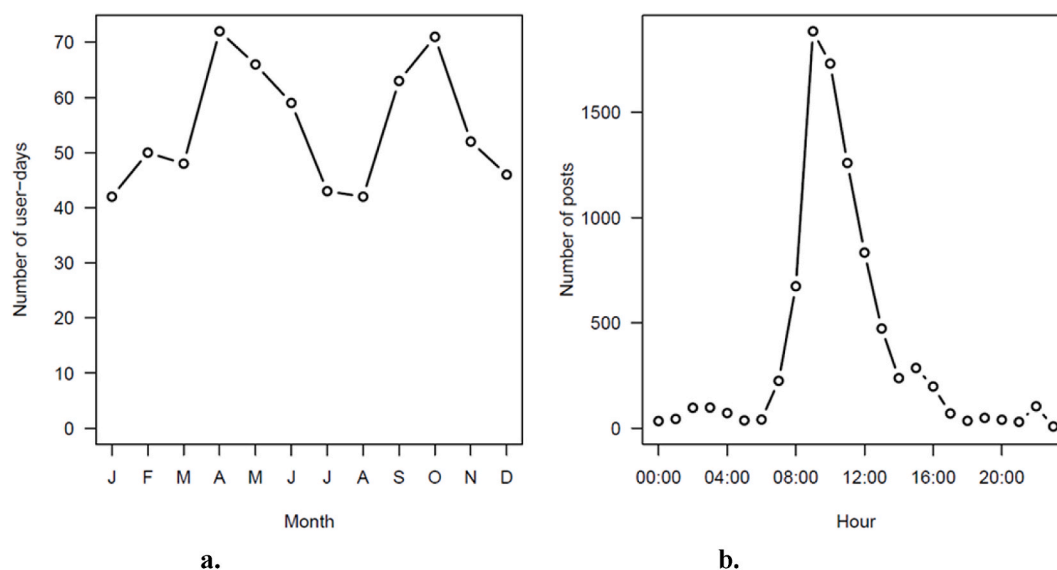
recreational activities is found for domestic visitors than for international visitors, and for male visitors than for female visitors (see Supplementary Material F). Among recreational activities, physical activities (e.g., sports) and experiential activities (e.g., picnicking, outdoor games) prevail, respectively, for Hebrew and Arabic speakers.

Tags related to the park’s wildlife appear more prominently for local visitors than for other groups (Fig. 6). Regarding wildlife, we observe differences between female visitors, for whom tags related to birds are associated with a higher TF-IDF score, and male visitors, for whom tags related to amphibians and insects feature more prominently.

Tags related to the park’s wildlife score higher for international tourists than for domestic visitors. The latter are more often characterized by tags related to the park’s flowers, especially for what concerns visitors from Haifa district. Compared to other groups, tags related to birds in the park featured more prominently for the group of Russian speakers.

### 3.4. Practitioners survey results

Based on the responses collected from the practitioners’ survey we share the average values of the quantitative responses in the survey, separated between those related to the analysis of textual data and those derived from the analysis of photographs and metadata (Table 7). All



**Fig. 5.** Monthly distribution of user-days as a proxy of the number of visits over the year (a) and average time of the day photographs and texts were taken or written, as a proxy of distribution of the visits across the day (b).

average values for single questions are presented in Supplementary Material G. Responses of the practitioners to the newness, helpfulness and validity of the information derived from the analyses of texts and photographs are summarized in Table 7. From the responding practitioners, we see that, on average, the statements derived from information from texts were not considered particularly new, although the information derived from the photographs and metadata was. For information derived from both data sources, the results were considered helpful to their work, with those statements drawn from text analysis being more so than those from the photograph and metadata analysis. The practitioners found that most of the statements made sense and were thus valid.

Practitioner assessments of the results from our analysis of social network data are presented in Fig. 7 using the analytical framework for assessing the newness, utility and validity of these results (Fig. 3). Assessments are presented for information derived from textual data (Tables 4–6, Supplementary Material D), metadata and photographs (Fig. 6 and Supplementary Material D), and for both data sets together. The labeling of the response for each question is presented in Supplementary Material G. The most positive responses were for information that the practitioners found “new”, “valid”, and “reinforcing”, or what we termed “breakthrough”. Five statements, representing both textual and metadata/photograph data sources, were suggested to be providing “breakthrough” knowledge (Fig. 7). One statement drawn from the text analyses was thought to be “counterintuitive” (new and helpful, but not necessarily logical or making sense), and two statements drawn from the metadata and photographs analysis were found to be “interesting” (new and valid), but not necessarily helpful.

Practitioners were also asked to comment regarding the summary produced by ChatGPT from the quotations coded by the Open AI with the keyword “flora”. They noted that the text was generally accurate, although it provided mostly information related to the memorial garden and not many insights regarding the surrounding nature park. Overall, the respondents were not very surprised with the content of the text, noting that the information was what they would have expected. They reported some inaccuracies regarding the mention of three different trails, which were presented as part of the memorial garden in the description, but which are instead in the nature park (i.e., incorrect association of walking routes), or misidentified species of plants and flowers. The first inaccuracy might be since the narrative did not distinguish between Nature Park and Memorial Garden. That distinction was not possible from the dataset as few data also had a precise

geographical location included, as such all the information contained in quotation referred to either of the two areas or to both together. One practitioner noted that the ChatGPT narrative placed too much focus on iris flowers as, according to the respondent, the species in the park are not particularly impressive as they have a very short blooming period. One respondent said that the text was more than he/she would have expected. The other respondents were not particularly impressed but appreciated the variety of the adjectives used in the narrative to describe flora in the park.

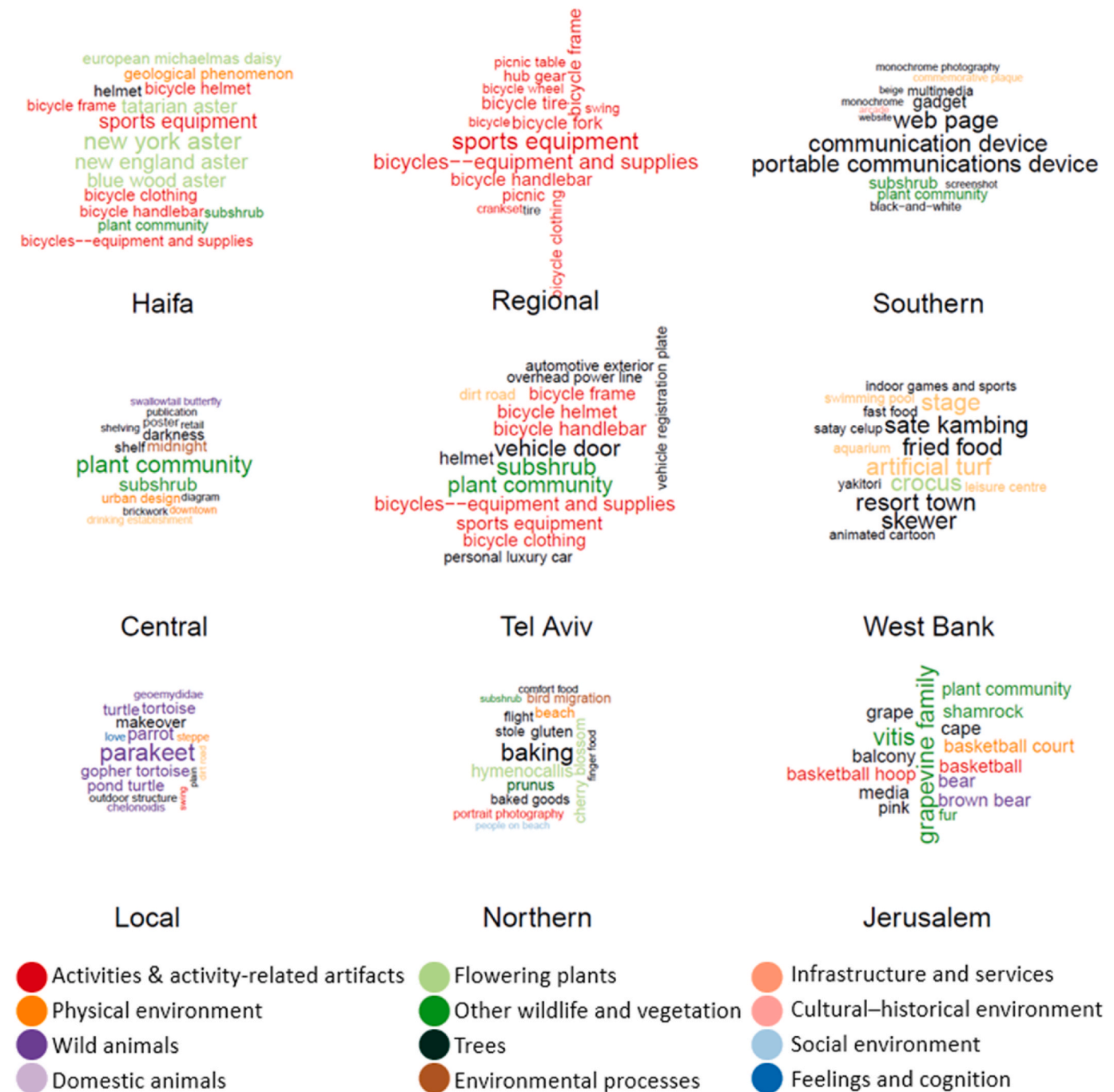
When asked if the text could have any application in their professional tasks, most of the respondents identified different possible applications such as capturing the feedback of visitors about a specific project and producing an online brochure about Ramat Hanadiv to be distributed to researchers or other guests from abroad in preparation for their visit. Other respondents commented that the staff’s perspectives on sustainability issues do not emerge in the ChatGPT text, suggesting that more effort would have to be made in educational and outreach to better convey sustainability principles to the public, especially during guided tours.

### 3.5. Additional feedback from the practitioners

Additional feedback from staff handling visitors, marketing, and education in the park highlighted that the research clarified which topics and values resonate with visitors. They found the social media data particularly useful in understanding visitor distribution, including origin, app usage, language, and gender. For example, they found surprising that 32.4 % of the people who shared content about Ramat Hanadiv were international visitors, while they estimate that only 5–15 % of the total visitors are from outside. This suggests a potential bias in the data towards international visitors, who post information about their visits to social networks more frequently than local or national visitors (see also Depietri et al., 2021). On the other hand, the spatial distribution of the geolocated posts confirmed the practitioners’ prior knowledge about where the visitors spend most of their time in the park (e.g., gardens, marked paths in the park, springs, and the park’s archaeological sites). The staff were surprised by the variety of languages in the tags, with Hebrew accounting for only about 47 %, while the temporal and spatial patterns largely aligned with their expectations of visitor loads throughout the year and daily peak hours.

Although a large fraction of positive reviews was expected, managers noted that the typical feedback they receive - such as ‘amazing’ or ‘just





**Fig. 6.** Top 15 machine tags, ranked by TF-IDF score, for domestic visitors from different regions, classified according to the aspect of recreation they reflect, if any. Tags in black are not associated with any aspect of recreation.

like in Europe' - is too general to be useful. The big data approach from social media offered instead detailed insights into the specific factors driving positive and negative emotions in visitors, such as which elements in the landscape evoke positive emotions and what specific emotion. Visitors appreciated the flowers, dense vegetation, water elements, art, the garden of scents, and seasonal changes. This feedback may help managers enhance these features to boost positive visitor experiences year-round. For example, the recent introduction of wild plants to the Memorial Garden received mixed reactions, with some appreciating the change while others viewing it as neglect. Managers also learned about the important role of built elements and artistic installations in generating positive emotions and experiences in the public. This may inform future decisions to introduce similar elements into the

nature park as part of a new strategy of "reconnecting man and nature". An "environmental art trail" going out into the nature park, for instance, could help overcome psychological barriers for visitors who are less inclined to hiking and thus tend to stay in the Memorial Garden and in the visitor center.

Staff members deemed it valuable to read information about the negative comments and what aspects of park visits motivated those comments. For example, learning that visitors were bothered by specific park rules forbidding certain activities in the park suggested that the managers of the park could present these rules in a more positive way. Negative feedback is very rarely collected from park visitors with other methods used previously. Despite being a small fraction of the overall feedback, this information may prove particularly useful in defining

**Table 6**  
ChatGPT elaboration for the report of the quotations under the group "flora".

Group: FLORA	
Summary	Quotations: 90
Names of gardens	Query: Please provide the names of the gardens mentioned in the text. Certainly! Based on the texts provided, the following gardens were mentioned: 1 Rothschild's Memorial Gardens 2 Ramat Ha-Nadiv Gardens Within Ramat Ha-Nadiv Gardens, specific areas or gardens mentioned include: ● Fragrance Garden ● Rose Garden ● Palm Garden ● Waterfalls Garden ● Mediterranean Waterfall Garden ● Engagements Garden ● Ficus Garden These gardens showcase a variety of flora and landscapes, contributing to the overall beauty and thematic richness of the locations.
List of species	Query: In the texts provided please extract the names of plants, flowers and trees mentioned. Based on the texts provided, the following names of plants, flowers, and trees are mentioned: ● Rosaria ● Irises ● Dracaena ● Banyan ● Roman pines ● Roses ● Fragrant herbs ● Spices ● Lily of the flowers ● Beach lilies ● Mediterranean plants ● Palm trees ● Ficus trees These are some of the specific references to botanical elements found in the texts.
<p>Query: Please produce a summary of 300 words of the three summaries you produced, focusing on flowers, plants and trees.</p> <p>Rothschild's memorial gardens in Ramat Ha-Nadiv offer a captivating experience for visitors, particularly those interested in flowers, plants, and trees. The gardens are meticulously cared for and boast a diverse collection of flora. The best times to visit are winter and spring, when vibrant blooms of rosaria and irises create a lush and refreshing atmosphere.</p> <p>The gardens feature themed areas, including a classic European rose garden, a Mediterranean waterfall garden, and a fragrant spice garden. These well-groomed and well-maintained gardens are a testament to the dedication and investment put into their design. Visitors can explore the gardens along three circular routes, with maps available at the info center.</p> <p>The gardens offer a sensory delight, with a designated aroma garden and scented corners filled with fragrant herbs and spices. The gardens showcase a range of trees and plants from different parts of the world, such as dracaena, banyan, and Roman pines. These exotic additions add to the beauty and diversity of the landscape. Additionally, the gardens are well-equipped with facilities, including toilet complexes, a kiosk, a picnic grove, and a playground, ensuring a comfortable and enjoyable visit for families.</p> <p>Visitors commend the well-maintained landscapes and the meticulous care given to the gardens. However, some suggest the inclusion of more signage to identify the various plants and trees. The gardens offer a European-style ambience, with water canals, fountains, and a solar clock enhancing the visual appeal.</p> <p>Overall, Ramat Ha-Nadiv's Rothschild memorial gardens provide a serene and enchanting experience for nature lovers. The gardens' well-groomed landscapes, diverse plant collections, and inclusive design make them a must-visit attraction. Whether strolling through the rose garden, enjoying the fragrant spices, or marveling at the exotic trees, visitors are sure to be captivated by the beauty and tranquility of these remarkable gardens.</p>	

future management strategies. Staff appreciated that the proposed approach provides unfiltered, unintentional insights, offering valuable learning compared to traditional tools (e.g., surveys). While biases exist in both methods, they can also serve as complementary tools.

Regarding the demographic analysis of the photos, it has great design and planning potential. For instance, it is good to know what generates positive emotions in women and men or in children, for speakers of different languages, locals versus national or international audience. Despite this, some of the information derived from the analysis nonetheless was confusing, and thus not considered useful. For instance, park staff noted terms such as "headstone", "monument", "baluster", "dome", and "statue" which they could not identify or connect to specific elements in the garden or park.

4. Discussion

4.1. Capturing visitors' emotions through social media data

Our study, based on a large amount of social media data, identified how most of the emotions expressed by visitors of the Ramat Hanadiv Natural Park and Memorial Garden were positive rather than negative. This is in line with most of the available studies that analyzed emotions generated by natural park visitors from social media data. Positive emotions identified in previous studies included anticipation, trust and joy (Mangachena & Pickering, 2021). According to another study, happiness and appreciation of beauty were the common positive emotions followed by love, calmness, and surprise (Roberts et al., 2018).

Positive emotions of visitors are often associated with specific landscape attributes (Huai & Van de Voorde, 2022; Komossa et al., 2020), such as the area of the park, the mean patch size of water bodies (Kong et al., 2022), the Normalized Difference Vegetation Index (NDVI) (Zhu et al., 2021) or the Panoramic Green View Index (PGVI) (Huang et al., 2022). Our elaborations allowed us to broaden the categories of factors that can be linked to the rise of positive emotions in visitors, going beyond elements of the landscape to encompass recreational activities, cultural events, sense of place, connection with history, the quality of management of the area, its services, signage, cleanliness and the atmosphere of the place, shade, and comfort of the area.

Generally, only a small occurrence of negative feelings is recorded in these studies (Hausmann et al., 2020; Huai & Van de Voorde, 2022). In natural parks, the literature reports, for instance, fear and anger followed by sadness and disgust (Roberts et al., 2018). Negative emotions are generally associated to safety and crime (Mangachena & Pickering, 2021), lack of cleanliness (Huai & Van de Voorde, 2022), crowdedness (Huai & Van de Voorde, 2022; Niezgoda & Nowacki, 2020), fear of dangerous animals (Mangachena & Pickering, 2021), or to dislike of impervious surfaces (Kong et al., 2022; Zhu et al., 2021). Negative emotions also seem to be associated with events or experiences occurring within the green space, rather than being in response to the green spaces themselves (Roberts et al., 2018). Our study confirms these results while providing additional sorts of information regarding negative emotions that can be useful to park managers. For instance, it was possible to collect detailed feedback on negative emotions of visitors related to entrance fees, opening hours, recreational infrastructure, park policies and restrictions, customer service, accessibility, availability of

**Table 7**  
Summary data of the survey responses regarding statements derived from the text analyses and the photograph and metadata analyses.

Type of analysis	New	Helpful	Makes sense
Information derived from text analyses	3.40	4.50	4.90
Information derived from photograph and metadata analyses	4.30	4.00	4.90
All	3.85	4.25	4.90

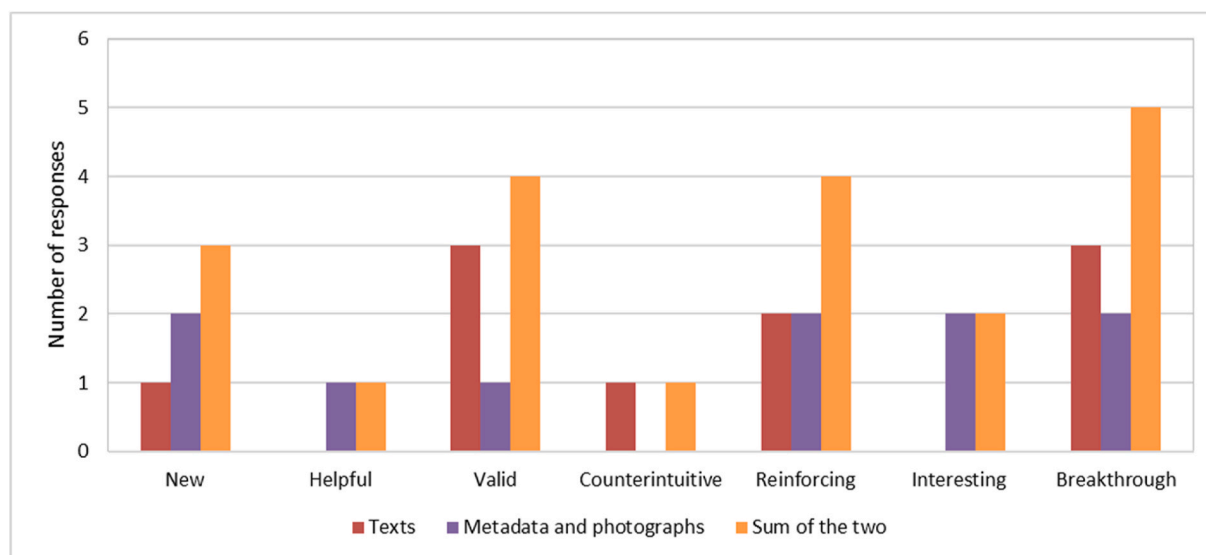


Fig. 7. Labeling of the results of the survey based on Fig. 3.

the information, conditions of the trails, perceived neglect of some areas of the park, and nuisances from animals and insects.

Overall, the present study, thanks to the use of OpenAI functions in Atlas.ti and ChatGPT, greatly broadens the array of information that can be captured from social media textual data, both in terms of the number and in the types of emotions that can be investigated, including what triggers these emotions and why. It also saves months of manual coding work. As such, the information that can be derived from textual data from social media, can now support natural park planning and management far beyond the connection that is traditionally investigated between landscape features and the emotional response from visitors. Despite this, these methods still produce inconsistent information, in our case based on artifacts and peculiarities in the input data, that can only be identified by researchers familiar with the park and its characteristics. So, results generated by automated platforms such as ChatGPT still require an informed human assessment and validation.

The analysis of photographs focused on the differing references among and between demographic groups (i.e., international versus internal, differences within Israel, gender, language). Previous research from social media data has demonstrated that landscape preferences change under different cultural backgrounds (Chen et al., 2022; Huai & Van de Voorde, 2022). Significant differences in human demand under a linguistic background exist when comparing human emotions in different types of urban green spaces supply through sentiment analysis. This research found that natives and immigrants have different cross-cultural demands (Chen et al., 2022). Survey in 33 parks located in four European capitals (Helsinki, Berlin, Bucharest and Lisbon) revealed clear differences in motivations and enjoyments between cities, implying that the day-to-day practices of people using and experiencing nature varies between cities (Vierikko et al., 2020). Indeed, the relationship between people and nature is a particularly culturally sensitive narrative according to some (Simmons, 1993). In our case, the types of activities or landscape attributes of interest were also different depending on the provenance, language, and gender of the visitors.

The possibility to adequately identify emotions through social media data also seems to be subject to some deviations between public emotions quantified by social media data and real public emotions people actually experience (Kong et al., 2022). Attention should therefore be paid to the reliability of social media data in quantifying public emotions or the extent to which they reflect the mood of the population (Zhu et al., 2021). For instance, a bias might be introduced by the fact that people tend to share their positive and optimistic images with others on their social network platforms (Calcagni et al., 2022). In our study we

were nonetheless able to collect significant information of what causes negative emotions to park visitors, meaning that not all unpleasant emotions go uncaptured by the method.

Regarding the method, the feedback from the managers collected with the survey suggests that the new information derived from the two data sets (texts and photographs) can validate existing knowledge regarding visitors' emotions and experiences, but it also introduces new information that can contribute to more focused management of park resources to tailor infrastructures to visitor preferences and to generate more positive emotions. Visitors' preferences and demographics were deemed particularly useful by practitioners, while the information regarding negative emotions, despite representing only a small fraction of the emotions expressed by Ramat Hanadiv visitors, generated curiosity and could provide insights on how to improve the management of the park. On the other hand, social media data, especially if not adequately geotagged, might introduce some nuisance and bias in the data that might confuse the practitioner, for instance regarding what elements of the landscape visitors are referring to.

#### 4.2. Additional methodological considerations

Other limitations of social media data can be introduced if the study relies on only one single social media source or platform (Cui et al., 2021), such as with Flickr (Cao et al., 2022; Mouttaki et al., 2022) or texts from Twitter (Bhatt & Pickering, 2021). Such a reliance on only a few data sources can result in a sample less representative of the population of park visitors. As is demonstrated here and in previous research (Ghermandi et al., 2023), specific population groups may use one social network platform more than others. By analyzing user-generated content from 13 different platforms we intend to reduce this bias significantly. By integrating multiple sources of data, each social network platform appeared as able to capture a particular sub-segment of the global population of park visitors. As such, the combined use of data derived from multiple platforms allowed us to capture a more representative sampling of park visitors. Disadvantages include that this is a time-consuming task, requiring in some cases manual retrieval due to the restrictive Terms of Service that characterize some of the platforms investigated.

Due to the limitations in the way the different platforms can be searched, as well as due to potential errors in the geotagging of the pictures and texts, some of the data items may refer to areas in the proximity of the park, but not within the park itself. However, since these are seemingly in small numbers, this is not expected to

substantially affect the results of most of the analyses performed but might affect the outcome of the TF-IDF analysis as this method particularly emphasizes less frequent data entries. For instance, tags referring to horse riding (e.g., "stallion", "mare") which appear in the gender analysis (Fig. F3 in Supplementary Material F), likely refer to recreational activities that are known to occur in the surroundings of the park but are not allowed within its boundaries.

Furthermore, while we advocate for the many advantages of the use of AI, we also emphasize that its use - at least regarding the most recent AI applications - still demands close interaction with, and fine-tuning by, human researchers. In the case of the analysis of texts, employing OpenAI applications, it is assumed that automated AI-based coding reduces the time needed for analysis (Karasov et al., 2020). However, coding qualitative data with ChatGPT and the use of OpenAI seems to be better adapted to classifying short texts generated with social media data than interviews or long texts. Indeed, the automatic generation of the codes can mean that the researcher loses grasp of the whole narrative of the text, particularly in the case of interviews, as reports from the quotations can be fragmentary, devoid of broader context, thus leading to a poorer understanding of the responses. This requires the researcher to go back and re-analyze the original text, which prolongs the analytical process (Frieze, 2023). In addition, coding with OpenAI functions can generate codes in the number of thousands, as in our case and as also highlighted by Frieze (2023). In this way, some time that is saved in coding is needed to reorganize and regroup codes. Nonetheless, in the case of big data from social media, the time spent reorganizing and regrouping codes remains minimal when compared to the time one would spend in coding these large amounts of data manually.

Also, the codes attributed through the automated coding might sometimes not result as being fully informative and it might be required to investigate the original data to make sense of them (Frieze, 2023). In the case of our study, we did a preliminary check on a sample of quotations to see if the right codes were assigned by the OpenAI function. From this analysis it resulted that the codes assigned reflected the subject of the texts, although some inaccuracies were identified. The grouping we performed in overarching groups of codes reduced some of these biases and allowed us to produce results that appeared mostly adequate, also to the eyes of the practitioners.

In terms of replicability, there are some limitations with the automated coding with the OpenAI. This, if repeated on the same data, can give a significantly different set of codes from the previous coding. As such, replicability is very limited, further highlighting the need for human review and validation at each stage of the analytical process. Previous research additionally highlighted that coding might contain biases since the OpenAI is trained on a specific set of data and this is undisclosed (Siiman et al., 2023). As such, human involvement and judgment is needed to align the coding to the objectives of the research (Siiman et al., 2023).

The use of ChatGPT to analyze qualitative data and to summarize contents from reports have already been identified as potentially able to improve research and save time (Lund & Wang, 2023; Tabone & de Winter 2023), while increasing transparency (Siiman et al., 2023). However, others have highlighted the limits in terms of interpretative meaning that a summary produced by ChatGPT contains (Morgan, 2023). According to Morgan (2023, p. 8) "there is no substitute for knowing one's data and using that knowledge in the inherently subjective process of making meaning from that data". ChatGPT could nonetheless be used as an assistant, but knowledge of the data remains indispensable.

In ChatGPT, it appears that the way the query is formulated can have a great effect on the resulting quality and focus of the summary. Providing background information to ChatGPT before the query can indeed improve the quality of the outcomes of the requested elaboration of the data (Siiman et al., 2023). Despite this, the elaborations we obtained from ChatGPT were adequate with respect to the objectives of our study, as confirmed by the responses of the practitioners. In terms of

costs, most of the commercial AI suppliers offer extended academic licenses for research purposes (Egarter Vigli et al., 2021). Limitations of the OpenAI might be related to cybersecurity and data management risks (Nishant et al., 2020). The privacy of individuals whose datum was used to train the model and the ethical implications of creating highly realistic synthetic text or speech, can arise these could be used to impersonate or deceive others (Lund & Wang, 2023).

#### 4.3. Management implications

The proposed approach provides new and important information on both the positive and negative emotions of visitors regarding their experience of the park in much greater detail with respect to other methods. This supports park managers in the design of more specific and tailored interventions to improve the overall experience of nature. The diversity of visitors' emotions that could be identified was new and helped envisage interventions that would trigger specific positive emotions. This method also allowed them to think about what generates and how to reduce negative emotions that people expressed in social media, although these were recorded in a much smaller percentage with respect to positive emotions. Negative feedback was particularly precious because it was rarely recorded by methods previously used. Additionally, park managers expressed interest in the variety of questions that could be asked regarding the data, although this required a follow-up project.

Demographic information was particularly useful to better understand the provenance of the users, gender and languages spoken. The analysis of the photographs elaborated on different demographics also provided potentially very interesting information to support planning. However, the noise in the data was thought to be too large and the results were at times difficult to interpret. Detailed information regarding management implications is provided in sections 3.4 and 3.5.

#### 5. Conclusions

In this study we used a large database of social media data (both texts and photographs) to assess visitors' positive and negative emotions and what triggers them in support of the management of the Ramat Hanadiv Natural Park and Memorial Garden in Israel. We also investigated and noted differences in preferences according to some demographics of the visitors, such as the provenance, language, and gender. Innovative aspects of the paper reside in the use of AI from the analysis of a large database of texts and photographs. This vastly increases the flexibility in the choice of themes that can be analyzed. In our case, the research was also conducted as an interactive and collaborative project with the managers of the park. Some of the results appeared as potentially finding applicability in supporting the management of the park, such as that information that reflected negative emotions, as these were less known to managers and for this reason resulted more helpful. Knowing about visitor demographics and preferences was also particularly useful for management purposes. Finally, some noise in the data can hamper the usefulness or applicability of the results, underscoring the continued need for human interaction and honing of AI output.

#### CRedit authorship contribution statement

**Yaella Depietri:** Software, Formal analysis, Visualization, Investigation, Writing – original draft, Methodology. **Andrea Ghermandi:** Supervision, Funding acquisition, Conceptualization, Visualization, Methodology, Data curation, Writing – review & editing, Software, Formal analysis. **Liat Hadar:** Writing – review & editing, Conceptualization, Funding acquisition, Resources. **Daniel E. Orenstein:** Methodology, Supervision, Conceptualization, Writing – review & editing, Funding acquisition.



## Management implications

The proposed approach provides new and important information on visitors' positive and negative emotions in much greater detail with respect to other methods. This supports park managers in the design of more specific and tailored interventions to improve the overall experience of nature. Also, the diversity of emotions that could be identified was new to practitioners and helped envisage interventions that would trigger specific positive emotions. The method also allowed them to think about how to reduce negative emotions that people expressed in social media, although these represented a much smaller proportion of the emotional response of visitors.

Demographic information was particularly useful to better understand the provenance of the users, gender and languages spoken. The analysis of the photographs elaborated on different demographics also provided potentially very interesting information to support planning based on visitors' preferences. However, the noise in the data was thought to be large and the results were at times difficult to interpret.

## Declaration of competing interest

We warrant that all of the authors have agreed to this submission and none of the authors has any conflict of interest in regard to this manuscript. Also, we warrant that this manuscript is the original work of the authors listed and has not previously been published. It is not submitted to any other journal at this time. All the figures are original work. There are no disputes over the ownership of the data presented in the paper and authors agree with contributions attributed in the paper.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jort.2025.100923>.

## Data availability

The data that has been used is confidential.

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