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TOURISM INTELLIGENCE AND ONLINE EMOTIONS: SENTIMENT ANALYSIS IN BOUTIQUE HOTELS OF PUEBLA

TOURISM INTELLIGENCE AND ONLINE EMOTIONS: SENTIMENT ANALYSIS IN BOUTIQUE HOTELS OF PUEBLA

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Abstract-- In a context of digitalized and competitive tourism, Tourism Intelligence (TI) leverages Big Data from online reviews to improve strategic decision-making and promote hotel sustainability. This study quantitatively analyzes tourist satisfaction in 20 boutique hotels in Puebla (Mexico), characterized by their unique design and cultural roots, by examining the emotional dimensions of the digital experience (web UX).

Using a quantitative, non-experimental, cross-sectional, and correlational design, 1,464 reviews collected in June-July 2025 from TripAdvisor, Booking.com, and Google Reviews were processed. Predominant feelings and emotions were classified using natural language processing (NLP) techniques based on transformer models (RoBERTuito and BETO).

The results reveal a clear predominance of positive feelings (69.7%; n=1,021), compared to negative (16.3%) and neutral (14.0%) feelings. The most frequent emotion was joy (52.4%), while disgust and anger accounted for 18.2%. The average length of the reviews was only 16.3 words. Significant correlations were identified between dissatisfaction and aspects such as accessibility and quality of service.

The study validates the use of sentiment analysis within IT to generate predictive knowledge, confirm mostly positive perceptions, and strengthen emotional ties with boutique hotels. It recommends implementing real-time monitoring such as ReviewPro and longitudinal studies to reduce seasonal biases, thereby contributing to more responsible, competitive, and sustainable tourism in Mexico.

Keywords-- Tourism Intelligence, Sentiment Analysis, Opinion Mining, Boutique Hotels, Web User Experiences.

Abstract-- In a context of digitalized and highly competitive tourism, Tourism Intelligence (TI) leverages big data from online reviews to improve strategic decision-making and promote sustainability in the hotel sector. This study quantitatively analyzes tourist satisfaction in 20 boutique hotels in Puebla (Mexico), characterized by their unique design and deep cultural roots, through the examination of the emotional dimensions of the digital experience (web UX). Using a non-experimental, cross-sectional, and correlational quantitative design, 1,464 reviews collected between June and July 2025 from TripAdvisor, Booking.com, and Google Reviews were processed. Through natural language processing (NLP) techniques based on transformer models (RoBERTuito and BETO), predominant sentiments and

emotions were classified.
The results reveal a clear predominance of positive sentiments (69.7%; n=1,021), compared to negative (16.3%) and neutral (14.0%) ones. The most frequent emotion was joy (52.4%), while disgust and anger together accounted for 18.2%. The average review length was only 16.3 words. Significant correlations were identified between dissatisfaction and aspects such as accessibility and service quality.
The study validates the use of sentiment analysis within Tourism Intelligence to generate predictive insights, confirm predominantly positive perceptions, and strengthen emotional bonds with boutique hotels. It is recommended to implement real-time monitoring with ReviewPro and longitudinal studies to reduce seasonal biases, thus contributing to a more responsible, competitive, and sustainable tourism model in Mexico.
Keywords-- Tourist intelligence, Sentiment Analysis, Opinion Mining, Boutique Hotels, Web User Experiences.

INTRODUCTION

In an increasingly digitized and competitive tourism landscape, the management of destinations and hotel establishments requires innovative tools capable of capturing and interpreting the voice of the visitor in depth, turning it into actionable information. Tourist Intelligence (TI) is consolidating itself as a strategic approach that incorporates the analysis of Big Data derived from online reviews, social networks, and rating platforms, transforming data into knowledge that guides decision-making, improves profitability, and promotes sustainability (Gallego, 2022). In this context, sentiment analysis and opinion mining are fundamental advances in natural language processing (NLP), as they enable the quantification of emotions and subjective attitudes expressed by users in web environments, allowing for the evaluation of tourist satisfaction beyond conventional indicators such as numerical scores (Álvarez, 2019).

Boutique hotels, defined by their unique design, personalized service, and genuine connection to local heritage, have experienced remarkable growth in Mexico, especially in destinations such as Puebla, where they integrate colonial elements with contemporary offerings (Giménez, 2025). However, despite their appeal to tourists seeking exclusive experiences, it remains difficult to quantitatively measure the emotions implicit in digital reviews, which often reveal nuances of joy, surprise, or disappointment that impact online loyalty and reputation. In Puebla, with more than 20 boutique hotels located in the historic center, such as La Casona de la China Poblana or Hotel Cartesiano, platforms such as TripAdvisor, Booking.com, and Google Reviews accumulate thousands of opinions that, through rigorous analysis, can reveal affective patterns and opportunities for operational improvement, in accordance with the fundamentals of Web User Experience (UX), which emphasize usability, attractiveness, and perceived value (Arhippainen & Tähti, 2003).

This research closes this gap through a quantitative design that uses transformer models such as RoBERTuito and BETO to analyze feelings and emotions in a corpus of 1,464 reviews obtained between June and July 2025 from 20 boutique hotels in Puebla. The main objective is to evaluate tourist satisfaction by identifying polarities (positive, neutral, and negative) and specific emotions (joy, surprise, sadness, anger, disgust, and fear), thus providing IT with predictive insights that strengthen competitiveness and service personalization. As a secondary objective, the correlation between these emotional dimensions and contextual variables such as location and service is examined, enriching the UX construct in digital tourism scenarios.

The structure of the manuscript is organized as follows: section 2 develops the central concepts of Tourism Intelligence, sentiment analysis, opinion mining, boutique hotels, and web user experience; section 3 describes the quantitative and computational methodology applied; section 4 presents the descriptive and correlational results; section 5 analyzes the theoretical and practical implications; and section 6 presents conclusions along with recommendations for future studies. In this way, the work not only quantifies tourist satisfaction, but also elevates it to an intelligent, emotional, and sustainable model, consolidating Puebla as a benchmark in hotel innovation.

Tourism Intelligence

Currently, tourist destination management is based on tourist intelligence (TI) strategies, which incorporate different approaches to understanding new management methods.

According to Gallego (2022), Tourism Intelligence consists of incorporating analytical tools based on global and up-to-date data to improve decision-making in the sector. It facilitates strategic management by capturing and analyzing relevant information from the environment, creating and sharing knowledge that allows for the formulation of appropriate strategies to improve profitability (Ghomi, 2021). Similarly, Villar (2024) defines it as the identification of opportunities and threats that generate predictions to obtain competitive advantages. TI offers direct benefits (risk reduction, useful information, avoiding redundancies, and strategic use of data) and indirect benefits such as early identification of opportunities/threats, increased business survival, increased turnover, better assessment of the bargaining power of tourists and intermediaries, and better understanding of environmental variables (Hanif, 2022).

The concept of "intelligence" implies a comprehensive view of all the elements that affect the competitiveness of the destination (Luque, 2015), with an "intelligent" approach being essential to adapt to a complex, technological tourism ecosystem with an enormous volume of information (Celdrán, 2018). TI facilitates strategic management by analyzing information about the environment and generating knowledge and predictions that improve profitability and competitiveness (Ghomi, 2021). Real-time analysis, linked to Big Data, reduces errors and optimizes processes in a digital and globalized context.

The main types of tourism intelligence are: 1. Tourism Market Intelligence (Femenia & Baidal, 2021), 2. Tourism Competitive Intelligence (Sigala, 2018), 3. Territorial Tourism Intelligence (Buhalis, 2015), 4. Artificial Intelligence applied to Tourism (Ivanov, 2019), 5. Tourism Sustainability Intelligence (Gössling, 2016).

Among the main platforms are: TourMIS (TourMIS, 2006), STR Global (STR, 2022), ForwardKeys (Hotel tech report, 2020), ReviewPro (Guindo Design, 2025), and Mabrian Technologies (Mabrian, 2024), which are key tools for real-time data-driven decision-making and advanced analysis of tourist behavior.

Sentiment analysis

According to Álvarez & Ríos (2019), sentiment analysis in the customer experience refers to the process of analyzing data to understand and measure how a customer feels about a specific product, service, or brand. This data can be in written form and collected from spoken language. A company can use sentiment analysis metrics to understand other customer metrics, such as Customer Satisfaction Score (CSAT) and Net Promoter Score (NPS). This information can help redirect business operations, customer service, and business processes to improve the customer experience.

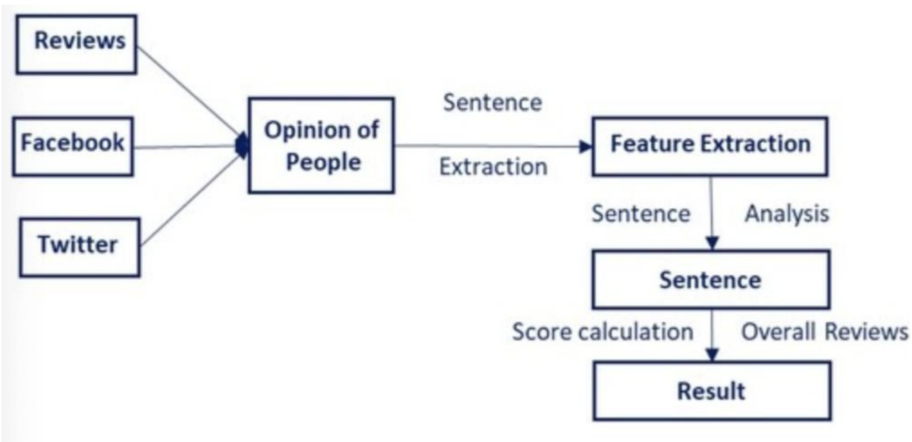
For Rosenbrock et al. (2022), sentiment analysis is a form of data science that uses artificial intelligence (AI), machine learning, and natural language processing (NLP) to analyze customer comments and reviews in real time across an organization. Sentiment analysis is specifically extracted from all types of interactions, such as support requests, surveys, product comments, and phone calls, among other types.

By using these interactions as data, a company can identify the key issues that customers are contacting them about and gain real-time insights into the sentiment behind each one. In addition, by analyzing these data points, an organization can identify the drivers of negative and positive sentiments and notice any fluctuations in customer sentiment.

The main goal of sentiment analysis in customer experience is to understand customers' feelings and emotions toward the brand. The sentiment analysis process can lead to the implementation of tools, such as chatbots or a reconfigured marketing strategy that introduces a targeted marketing campaign. Sentiment analysis is only one part of a broader customer experience (CX) strategy, which typically involves multiple components. All of the above aims to retain current customers and generate new, lasting relationships. There are four types of sentiment analysis: fine-grained sentiment analysis, emotion detection sentiment analysis, aspect-based sentiment analysis, and intent sentiment analysis (George, 2024).

The sentiment classification of the identified aspects, as presented in Figure 1, has to do with the classification of the multiple aspects of opinions gathered from online reviews, Twitter, Facebook, and other blogs that offer reviews of wellness destinations. (See Figure 1.)

Figure 1. *Multi-aspect opinion mining process*.



Source. *(George, 2024).*

By understanding a customer's mindset about their products or services and their intention to contact the company in relation to them, a company can intuit whether a customer intends to use a product. This means that the intentions of that specific customer can be tracked, creating a pattern that is used for marketing and advertising (George, 2024).

In addition, sentiment analysis can provide further insight by organizing tourist descriptions in terms of negative or positive ratings, based on their relevance and consistent use across all reviews (George, 2024).

Opinion mining

Sentiment analysis, also known as opinion mining, is a computational discipline that examines opinions, emotions, and attitudes expressed in texts. These opinions may refer to specific products, services, people, organizations, events, or topics. In this context, the term "object" is used to designate the entity being evaluated, which may include components (or parts) and associated attributes. Each component, in turn, may contain subcomponents and attributes of its own, forming a hierarchical structure.

Liu (2015) formalizes these notions through the following definitions: 1. Object: an entity, such as a product, person, event, organization, or topic, represented by a pair (T, A), where T is a hierarchy of components and A is a set of attributes of the object. Each component can have its own subcomponents and attributes. 2. Opinion: an assessment, emotion, or attitude, whether positive or negative, expressed toward a specific characteristic of the object.

Similarly, Opinion Mining (OM), also known as Sentiment Analysis, is a subfield of web mining that uses natural language processing, computational linguistics, and text mining techniques to identify and analyze subjective information expressed in user opinions. This is a relatively recent field whose relevance has increased considerably with the growth of e-commerce, blogs, forums, and social networks, as it allows valuable information to be extracted that can be classified as positive or negative (Webber, 2017).

For Pang & Lee (2008), the rise of e-commerce has changed consumer habits, as many people prefer to make their purchases and contracts online in a convenient manner, while sharing their experiences and opinions on different digital platforms. As a result, consulting reviews and comments before purchasing a product or service has become common practice.

However, although there are sites with thousands of opinions on the same article, the difficulty lies in identifying information that is truly useful for decision-making.

Similarly, for Shidore, Machh, Prashant & Bermade (2015), this field has progressively expanded and focuses on the analysis of subjective elements present in user-generated content. Its applications cover different levels of analysis depending on the task at hand. In general terms, there are two main approaches: 1. Polarity detection: this consists of determining whether an opinion is positive or negative. Beyond binary classification, a numerical value can also be assigned within a range, which is equivalent to obtaining a score or rating associated with the opinion. 2. Feature-based sentiment analysis: seeks to identify the different properties or attributes of a product mentioned in a review and establish the corresponding polarity for each of them. This approach is more complex and detailed than simple polarity detection.

Web mining is thus defined as a methodology that applies data mining techniques to retrieve and extract information from both the structure, content, and interconnections of a website and from users' browsing records (Zhang, 2008). This procedure is carried out by designing specialized algorithms and methods that facilitate the extraction of meaningful information from websites, enabling the development of e-commerce strategies geared towards personalized marketing (Grossmann, Hudec, & Kurzawa, 2005).

Boutique Hotels

Current accommodation options include hostels, traditional hotels, aparthotels, alternative accommodations, and boutique hotels, which are distinguished by their unique design and personalized service, adapting to different budgets and travel styles.

The boutique hotel concept emerged in the 1980s as a reaction to hotel standardization, offering differentiated experiences (Chan, 2012). The pioneer was "Blakes" in London (1978), with rapid expansion to the US and Asia; between 2011 and 2013, 23 new establishments opened in London (2,544 rooms) (Balekjian & Sarheim, 2011).

In New York, they stood out for their exclusivity, few unique rooms, and location in iconic buildings with a strong local identity. In Mexico, interest arose in the late 1990s alongside ecological and cultural tourism. In 1999, Hoteles Boutique de México was founded by Sylvie Latrie and John and Florence Youden (Casa del Poeta, 2016).

A boutique hotel is a luxury accommodation with fewer than 100 rooms, unique style, attention to detail, and an intimate atmosphere that reflects the local culture (Day, 2013), combining innovative architecture, exclusive services, and an authentic connection with the surroundings (Newton, 2021). They prioritize sustainability and community support (Giménez, 2025), differentiating themselves from lifestyle hotels by their greater exclusivity and individualization.

Key characteristics: small size (100 rooms) that favors entrepreneurship and short stays (Johns, Teare, & Aggett, 2007); innovative design that integrates the history and culture of the destination (Albazzaz, 2003); highly personalized service with high staff-to-guest ratios (Kurgun, Bağıran, Maral, & Ozeren, 2011); location in iconic historic buildings (Casa del Poeta, 2016).

Mexico City (CDMX) leads with 50 boutique hotels (Polanco, Condesa, Roma), followed by Quintana Roo (40 boutique hotels, with a sustainable focus in Tulum and Playa del Carmen), Baja California Sur, Jalisco, and the State of Mexico (20 each) (Boutique hotel, 2025). In Puebla and Guanajuato, restored colonial mansions are driving the segment with individualized attention (Unsal & Zeytinoglu, 2018). In Puebla, La Casona de la China Poblana (17th century), Hotel Cartesiano, and El Sueño Hotel & Spa (18th century mansion) stand out (El sueño, 2024).

Boutique hotels represent a global innovation that breaks with the standardization of large chains (Rǎbonțu & Niculescu, 2009). According to several authors, such as Johns (2007), Anhar (2001), Correia, Rita, and Moraes (2019), these hotels have recently gained great importance and popularity by focusing on specific markets where exclusivity, personalized service, luxury, and design are key to achieving the loyalty of demanding customers, responding to the demand for differentiation and niche segmentation (Melo, Barrera, & Franconetti, 2021).

Web User Experiences

User experiences are now a key pillar in the hotel industry, where travelers seek unique and personalized experiences beyond a simple stay.

Arhippainen and Tähti (2003) define it as the emotions, expectations of the user, and their relationship with people and context. Knapp (2003) describes it as "the set of ideas, feelings, and assessments of the user resulting from interaction with a product; it is the result of the user's objectives and cultural variables." The Chilean Promotional Marketing Association (2024) conceives it as the feeling, emotional response, and satisfaction derived from interaction with the product and its supplier.

In the web environment, IBM (2025) points out that a good experience seeks to generate pleasant feelings and loyalty. Norman (2004) presents it as "an integrating concept of all aspects of the interaction between the end user and the company, its services, and products." Bou (2003) advocates studying websites as services rather than products. The concept originated in marketing as brand experience (Kankainen, 2002) and has evolved from usability to include enjoyment and satisfaction (D'Hertefelt, 2002).

Brand communities strengthen loyalty and two-way communication (Bruhn, 2013). Users use hotel social networks to obtain information, make purchases, interact, entertain themselves, and express their identity (Wang, 2002). Studies by Kang (2011), Leung (2015), Vivek (2012), and Naumann and Bowden (2015) identify variables of perceived benefit and commitment.

From an economic perspective, participation depends on the benefits (information, relationships, belonging) outweighing the costs (time and effort) (Gu & Jarvenpaa, 2003). When the perceived benefits exceed these costs, the community increases its value and promotes its growth and sustainability (Butler, 2001).

Arhippainen and Tähti (2003) group the factors into five categories: user, social, cultural, context, and product. Kankainen (2002) sees it as the result of an action motivated in a context, influenced by previous and future expectations.

On the web, Morville (2004) proposes seven dimensions: useful, usable, desirable, findable, accessible, credible, and valuable. Mahlke (2002) highlights usefulness, ease of use, hedonic character, and visual appeal. UX is a multidimensional phenomenon that, by outweighing costs with benefits and focusing on usefulness, usability, and emotional value, generates engagement, loyalty, and sustainability in the digital hotel environment.

DEVELOPMENT

Method

This research was developed using a quantitative approach, employing advanced computational resources and natural language processing (NLP) techniques with a descriptive and explanatory scope. The study design was non-experimental, cross-sectional, and correlational, based on the extraction and analysis of pre-existing data on digital platforms. The unit of analysis consisted of a census covering all 20 boutique hotels in the city of Puebla, considering reviews and opinions generated on specialized sites (*TripAdvisor, Expedia,* *Booking.com, and Google Reviews*) and social networks during the period between June and July 2025. See Table 1.

Table 1. *Boutique hotels in the city of Puebla.*

Hotel	**Address**
Hotel Boutique Casa de la Palma	3 Oriente 217 Historic Center Puebla
Cartesiano Boutique Hotel	3 Oriente, Callejón de los Sapos. Puebla
La Perla Boutique Hotel	6 Sur 503, Historic Center of Puebla
La Casona de los Sapos Boutique Hotel	7 Oriente 406, Historic Center, Puebla
Azcami Boutique Hotel	C. 7 Sur 107, Puebla
Casareyna Boutique Hotel	Privada 2 Oriente 1007, Downtown, Puebla
Casona 65 Boutique Hotel	C. 2 Sur 907, Downtown, Puebla
El Sueño Boutique Hotel	Av. 9 Oriente 12, Downtown, Puebla
Casa Azulai Boutique Hotel	Av. 2 Oriente #808 Col. Downtown Puebla,
Milo Collection Boutique Hotel	11 Oriente 205, Downtown, Puebla.
Casona de la China Boutique Hotel Poblana	4 North Street, Downtown Puebla
Boutique Hotel Posada XVII	4 Sur 1103 Colonia Centro, Puebla
Casona de Santa Clara Boutique Hotel	6 East 212 Downtown, Puebla.
Casa Rosa Grand Boutique Hotel	16 de Septiembre 303, Historic Center, Puebla
Casa Monarca Boutique Hotel	7 Sur 303, Downtown, Puebla
Casa Pepe Boutique Hostel Puebla	Calle 6 # 27, Downtown, Puebla
La Quinta Esencia Boutique Hotel	9 Oreinte 16, Historic Center of Puebla.
La Violeta Boutique Hotel	8 Oriente 1202 corner 12 Norte Barrio del Alto, Puebla
Casa María Paz Boutique Hotel	C2 Norte 1406 Historic Center, Puebla
Andante Boutique Hotel	2 East #15, Downtown, Puebla.

Source: *TripAdvisor* (2025).

To ensure methodological robustness, complementary analytical and computational procedures were articulated. Text and opinion mining were applied as the main technique for processing large volumes of unstructured information, allowing the phenomenon to be broken down into observable variables. The computational architecture was based on deep learning algorithms, specifically implementing the RoBERTuito and BETO *transformer* models, both adjusted and optimized for the Spanish language.

The tests carried out included two levels of automated semantic classification:

1. **Sentiment analysis:** Objective categorization of opinions on positive, neutral, and negative valence scales.
2. **Emotion analysis**: Specific identification of the dominant emotion in the user's discourse, classifying them as joy, surprise, sadness, anger, disgust, and fear.

Finally, the descriptive correlational method analyzed the relationships between predominant emotions and associated variables (evaluations, location, and service characteristics), which determined correlations between the type of emotion and overall satisfaction. The research technique used for information analysis was digital content analysis, which was used to explore online reviews and opinions to identify feelings and emotions.

Results

The results of this study provide a quantitative description of the affective patterns detected in user reviews of boutique hotels in Puebla, using advanced natural language processing and sentiment analysis methods. These were organized into tables of frequency, intensity, and emotional distribution, which not only confirm the positive perception of this hotel category but also identify specific areas of dissatisfaction, offering empirical data for the design of operational and experiential interventions in the luxury tourism segment.

Table 2 summarizes structural characteristics such as sample size (n = 1,464), which guarantees statistical robustness for inferences about guest perceptions. The average length of reviews (16.3 words) is consistent with the rating format on digital platforms, where concise expression predominates.

Table 2. *Review indicator*.

Indicator	Value
Total reviews analyzed	1,464
Average word length	16.3

Platforms of origin	*TripAdvisor, Expedia, Booking.com, Google Reviews,* and social media.

Source: *Prepared internally based on data obtained from the Pysentiment program.*

Sentiment analysis results

Below are the quantitative results of the sentiment analysis extracted from user reviews of boutique hotels in Puebla.

Table 3 reveals a clear predominance of positive sentiments (69.7%; n = 1,021), followed by negative (16.3%; n = 238) and neutral (14.0%; n = 205). This distribution confirms widespread satisfaction with the boutique hotel offerings in Puebla. The proportion of negative reviews, although a minority, identifies a critical segment that requires intervention.

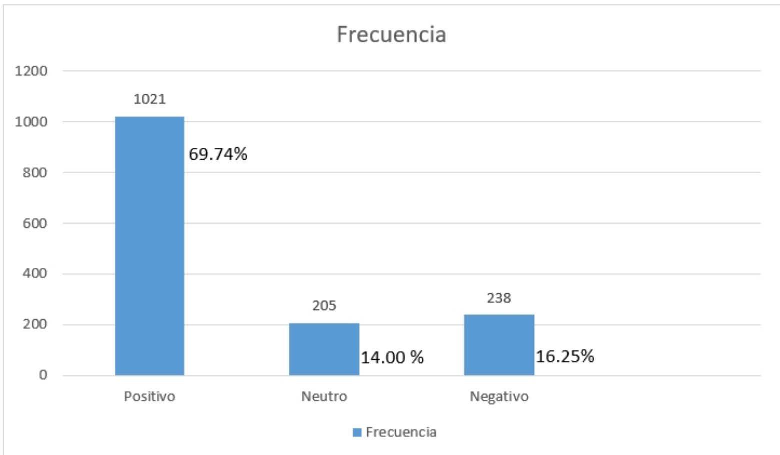
Table 3. Sentiment analysis in reviews

Sentiment	Frequency	Percentage
Positive	1021	69.74
Neutral	205	14.00
Negative	238	16.25
Total:	**1464**	**99.99**

Source: Prepared by the author based on data obtained from the *Pysentiment* program

The results of Table 3 are shown below (see Figure 2).

Figure 2. *Sentiment analysis*.



Source: *Prepared by the authors based on data obtained from Table 3.*

Emotion analysis results

The quantitative results of the emotion analysis extracted from user reviews of boutique hotels in Puebla are presented. These findings, obtained using natural language processing techniques, provide insight into both the overall assessment of the experience and the specific emotions underlying the opinions expressed.

Table 4 shows the emotion analysis detected in a set of reviews, presenting in a structured way the distribution, frequency, and intensity of the emotions expressed by users.

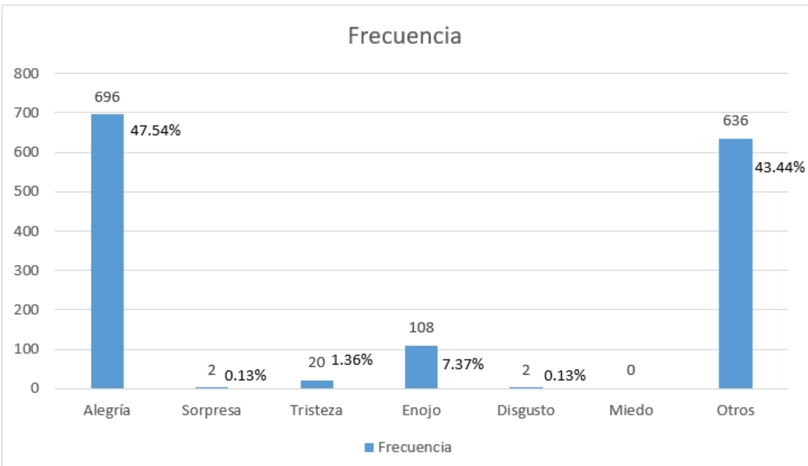
Table 4. *Emotion analysis in reviews.*

Emoción	Frecuencia	Porcentaje (%)
Alegría	696	47.54
Sorpresa	2	0.13
Tristeza	20	1.36
Enojo	108	7.37
Disgusto	2	0.13
Miedo	0	0.0
Otros	636	43.44
Total:	**1464**	**99.97**

Source: *Prepared internally based on data obtained from the Pysentiment program.*

The results of Table 4 are shown below (see Figure 3).

Figure 3. Emotion analysis



Source: *Prepared by the author based on data obtained from Table 4.*

Discussion

The results of this study strongly validate the integration of sentiment analysis and opinion mining within the framework of Tourism Intelligence (TI) as a strategic tool for quantitatively assessing tourist satisfaction in boutique hotels in Puebla. The predominance of positive reviews (69.7%) and the emotion of joy as the most frequent (52.4%; Table 5) confirm a mostly favorable perception of these personalized experiences, in line with previous research highlighting the value of online reviews for capturing spontaneous emotions in tourism. *Transformer* models such as *RoBERTuito and BETO*, adapted to Spanish, demonstrate their effectiveness in processing short reviews (average of 16.3 words), generating real-time *insights* that overcome the limitations of traditional methods such as surveys, which are prone to bias due to retrospective or unrepresentative responses. Furthermore, the correlation between negative emotions (16.3%, predominantly disgust and anger at a combined 18.2%) and operational variables such as location and service reinforces IT typologies, such as market and competitive intelligence, allowing early threats to be detected and profitability to be optimized (Femenia & Baidal, 2021).

From a practical perspective, these findings facilitate real-time monitoring through specialized platforms such as *ReviewPro and Mabrian Technologies* (Guindo Design, 2025), enabling agile interventions, for example, adjustments to personalized service to mitigate complaints about accessibility in historic mansions. This not only optimizes the personalization of experiences, which is key in boutique hotels with unique designs and a local focus (Day, 2013), but also promotes sustainable tourism by aligning operations with environmental and social impacts. Theoretically, the approach enriches the construct of Web User Experiences (UX) by incorporating multidimensional emotional dimensions (individual, social, and contextual), extending the integrative vision of user-provider interactions (Arhippainen & Tähti, 2003), and highlighting the differentiation of boutique niches from standardized chains (Johns, Teare, & Aggett, 2007).

However, the cross-sectional and non-experimental design implies limitations, such as seasonal biases derived from sampling from June to July 2025, which may not capture variations in periods of low demand, and non-response biases on platforms such as TripAdvisor, where extreme reviews predominate (Liu, 2015). This prevents causal inferences about temporal evolutions. For future research, longitudinal designs incorporating multimodal data and cross-destination comparisons with *hubs* such as Quintana Roo are suggested, along with predictive AI to simulate scenarios (Ivanov, 2019). Ultimately, this work advocates for the ethical adoption of these techniques in IT, promoting responsible, personalized, and competitive tourism that drives the sustainable development of the sector in Mexico and similar destinations.

CONCLUSIONS

This research illustrates the transformative potential of Tourism Intelligence (TI) by integrating sentiment analysis and opinion mining to quantitatively assess tourist satisfaction, focusing on boutique hotels in Puebla. The results show a predominantly favorable perception of guest experiences, with 69.7% positive reviews and joy as the predominant emotion (52.4%; Table 5), highlighting the ability of these accommodations to forge genuine and personalized emotional connections. Derived from a robust sample (n=1,464) processed with transformer models such as RoBERTuito and BETO adapted to Spanish, these findings not only confirm the superiority of online reviews in capturing spontaneous expressions compared to traditional approaches, but also identify priority areas for improvement, such as negative emotions linked to accessibility and service (16.3%), in line with IT typologies geared toward anticipation and strategic optimization (Femenia & Baidal, 2021). Theoretically, the results enrich the construct of Web User Experiences (UX) by incorporating multidimensional emotional dimensions that go beyond usability towards holistic satisfaction (Arhippainen & Tähti, 2003), and emphasize the differentiation of boutique hotels as sustainable luxury segments (Day, 2013). From a practical perspective, they facilitate the adoption of platforms such as ReviewPro and Mabrian Technologies for real-time monitoring, promoting agile interventions that increase profitability and competitiveness in destinations such as Puebla, where historical legacy is integrated with contemporary innovations.

However, the limitations inherent in cross-sectional design (including seasonal and non-response biases) highlight the relevance of more dynamic methodologies. In summary, this study advocates for the ethical and scalable implementation of these techniques in IT, promoting responsible tourism that fosters personalized, inclusive, and sustainable experiences. Future research could address longitudinal and multimodal approaches in cross-cultural contexts, consolidating IT as a pillar for tourism advancement in Mexico and Latin America. Ultimately, this approach not only quantifies satisfaction but also enhances it, positioning Puebla as a model of emotional and strategic hotel innovation.

FUTURE WORK

Based on the validation of sentiment analysis in Tourism Intelligence (TI) and recognizing the limitations of the cross-sectional design implemented, the following avenues are proposed to deepen scientific knowledge and practical application in the sector:

•Longitudinal Dynamics and Predictive Modeling with AI: To overcome the seasonal bias inherent in the June-July sampling, it is imperative to move toward longitudinal designs that capture fluctuations in satisfaction during periods of low and high demand. This line of research should integrate predictive artificial intelligence to not only describe the past, but also simulate future scenarios (Ivanov, 2019), allowing us to anticipate the impact of negative emotions on profitability and predict the effectiveness of operational adjustments, such as accessibility improvements in heritage buildings, before their implementation.

•Cross-Destination Comparative Analysis and Multimodal Approaches: We suggest expanding the geographic scope by comparing the performance of boutique hotels in Puebla with established tourist hubs such as Quintana Roo. This line of inquiry should be enriched by processing multimodal data (integrating text with images and video), which will strengthen the User Experience (UX) construct by capturing nonverbal emotional dimensions. This will make it possible to validate whether satisfaction patterns and complaints about services are systemic to the boutique segment or specific to the local cultural context.

Exploring these lines of inquiry will enable IT to evolve from a descriptive tool to a strategic and predictive one. By incorporating the temporal dimension and broadening the comparative spectrum, this research will consolidate a tourism management model in Mexico that not only quantifies emotion but also uses it as a driver for sustainable innovation and international competitiveness.

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