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Understanding destination brand experience through data mining and machine learning

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ABSTRACT

This research formalises a new methodology to measure and analyse Destination Brand Experience, improving upon traditional approaches by offering greater objectivity and rigour. Adopting a case study approach, five distinct and complementary types of analysis have been conducted: comprehensive sentiment analysis and topic modelling, an analysis using multiple thesauri, statistical analyses for hypothesis testing, and machine learning for classification. The methodological innovation, through the construction of thesauri, has enabled the measurement of sensory, affective, intellectual, and behavioural dimensions in unique and emblematic attractions, experiences, and transportation within a tourist destination, based on visitor reviews. This new approach allows tourism professionals and destination managers to identify areas for improvement and develop strategies to enhance tourist satisfaction. The findings suggest that there are significant differences in the relationships between specific dimensions and that gender and culture moderate or impact these relationships.

1. Introduction

Literature has demonstrated that destination branding provides a competitive advantage (Boo et al., 2009), and in this regard, understanding tourists' experience with a destination brand is crucial (Berrozpe et al., 2019; Rather et al., 2021; Kumar & Kaushik, 2020), as it encompasses aspects such as sensory, affective, intellectual, and behavioural (Barnes et al., 2014). The construct of Destination Brand Experience (DBE), first introduced by (Barnes et al., 2014) and derived from the general Brand Experience (BE) construct of Brakus et al. (2009), is a comprehensive model that captures these four essential dimensions of destination brand experience. DBE refers to the cumulative perception and emotional response that a tourist forms through direct or indirect interaction with a destination's brand identity. This encompasses all touchpoints, including cultural attributes, natural scenery, amenities, customer service, marketing communication, and personal experiences. As such, it plays a significant role in destination selection, satisfaction, and loyalty, profoundly influencing the overall success of tourism marketing strategies (Barnes et al., 2014; Boo et al., 2009; Kumar & Kaushik, 2018)

Destinations are complex products, not only because they combine various tourism-related offerings, but also due to consumers' subjective interpretation of them (Buhalis, 2000). The multisensory, fantasy, and emotional aspects of consumer behaviour in relation to products are particularly significant in the tourism industry (Govers et al., 2007; Hirschman & Holbrook, 1982). The application of the BE construct to tourist destinations presents a formal, rigorous, and systematic approach for assessing destination brand experiences. This comprehensive approach makes the DBE construct a valuable tool in the tourism industry for evaluating and enhancing travellers' experiences with destination brands (Barnes et al., 2014).

The paper highlights the prevalence of SEM and PLS in prior studies, emphasizing their utility in identifying and validating relationships between variables within DBE (Barnes et al., 2014; Bhattachary & Dutta, 2016; Boo et al., 2009; Khan & Rahman, 2017; Kumar & Kaushik, 2018).

However, the paper also raises methodological questions regarding the adaptability of these traditional techniques to the current context of abundant digital data sources, such as social media and online reviews, which have significantly expanded the volume of available data on brand experiences in tourist destinations (Westland, 2014). It questions the limitations of SEM and PLS in handling large data volumes and their capacity to detect non-linear patterns and complex interactions, hinting at the need for more agile and comprehensive methodologies.

The theoretical question addressed pertains to the evolving nature of

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DBE in the digital age and how traditional methodologies may not capture emerging trends or nuanced insights about shifting tourist preferences and perceptions (Barnes et al., 2014). The paper proposes data mining and machine learning (ML) as innovative alternatives. Data Mining is seen as a means to uncover meaningful patterns and relationships in large data sets, potentially revealing previously unnoticed facets of DBE. machine learning, with its adaptability and ability to handle unstructured data like text and images, is suggested as a powerful tool for gaining deeper and more dynamic insights into DBE. In the tourism industry, the utilisation of machine learning is becoming increasingly prevalent as an indispensable tool for ascertaining the most pertinent search query details and significantly enhancing the accuracy of forecasts in the realms of tourism and hospitality (Li et al., 2020). This growing trend is exemplified by studies such as those by Zhang et al. (2023) on destination perception and by Li, Lin, and Xiao (2022) on tourist demand.

Due to the limitations of traditional approaches in measuring and analysing DBE, it has been necessary to propose an innovative, complementary, and coherent methodology through four types of complementary analyses: sentiment analysis, topic modelling, an analysis with multiple thesauri, multiple statistical analyses for hypothesis testing, and a classification using machine learning, to achieve greater objectivity and rigour in measuring DBE. Given the growing importance of tourism and visitor experience in the perception and success of a destination, it is essential to develop methods that enable tourism professionals and destination managers to better understand and optimize the tourist experience.

Conversely, DBE, as a measurement tool, aims to quantify a destination's brand experience. Employing text analysis techniques like sentiment analysis and topic modelling, along with the implementation of machine learning techniques, it becomes feasible to measure and analyse DBE. This measurement enables researchers and destination managers to acquire insights into how tourists perceive and value a destination concerning their sensory, affective, intellectual, and behavioural experiences. Such measurement then facilitates the enhancement of the destination's management and marketing, empowering destination managers to devise more efficient strategies to boost the tourist experience and ultimately the perception of the destination's brand.

Following the introduction, this paper is structured as follows: Section 2 delves into the theoretical framework of the DBE dimensions used, as well as the concept of sentiment analysis. Section 3 details the methodology employed, covering research design, acquisition of selected data considering temporal, spatial, and category aspects, text preprocessing and cleaning, the use of a thesaurus, and sentiment analysis and topic modelling combined with statistical analysis techniques and data mining and machine learning. Section 4 presents the results, including sentiment analysis, comparison of the distributions of the studied dimensions through hypothesis testing, and as validation, the performance achieved by a machine learning classifier and the study of its metrics. Finally, this research concludes with Section 5, where conclusions, discussions, limitations, and future research directions surrounding the findings are offered.

2. Background

2.1. Theoretical framework

In the past few decades, the exploration of consumer experiences has consistently evolved. Brakus et al. (2009) formulated a robust framework to understand and analyse brand experiences across four dimensions: sensory, behavioural, intellectual, and affective. The forthcoming discussion will thoroughly explore these dimensions, referring to the contributions of several authors and studies cited in scholarly literature.

The Destination Brand Experience (DBE) construct originates from the brand experience theory proposed by Brakus et al. (2009), which conceptualises it into four dimensions: sensory, affective, intellectual, and behavioural. This theory underscores that tourists engage with the destination in a multidimensional fashion and posits that these interactions shape their comprehensive perception of the destination's brand. Hence, DBE, in its capacity as a theoretical construct, offers a holistic framework to comprehend how tourists perceive and experience a destination, and how these experiences mould their perception of the destination's brand. DBE has emerged as a focal point in tourism research over the past decade and beyond.

In 2008, a seminal study introduced a destination brand model, underscoring the significance of destination-specific elements in brand equity. This was particularly evident when tested with visitors to renowned destinations such as Las Vegas and Atlantic City (Boo et al., 2008). By 2011, the narrative's role in shaping destination brand experiences was accentuated, as evidenced by a netnographic analysis of travel blogs pertaining to South American cities (Colt, 2011). A shift towards a more holistic approach was observed in 2014, emphasizing the salience of sensory experiences within the DBE framework and its influence on revisit intentions and word-of-mouth referrals (Barnes et al., 2014).

Researchers addressing DBE have primarily adhered to a traditional approach and methodology, depending on surveys for their analyses. Prominent examples of this approach emerge in studies by Barnes et al., 2014; Singh & Mehraj, 2018; Singh & Mehraj, 2019; Rather et al., 2021; Khan & Fatma, 2021; Lin et al., 2023.

A distinct group of studies, encompassing those by Smith (2013) and Chen et al. (2014), has attempted to measure Brand Experience (BE) on social networks like Facebook. Yet, they only address some of the BE dimensions that Brakus et al. (2009) formulated or fail to differentiate them clearly. The study by Jiménez-Barreto et al., (2020) stands out, focusing on User-Generated Content (UGC) from platforms like Facebook and Twitter, which currently witness a clear decline in content.

It is important to note that while there are indeed studies that focus exclusively on addressing the Destination Brand Experience perspectives of Western destinations with surveys from solely Western participants, such as the study by Barnes et al. (2014) which utilized surveys from Swedish, Danish, and German visitors to analyse the Destination Brand Experience of the Swedish city of Lund, and the study by Boo et al. (2009) that assessed the Destination Brand Experience of the cities of Las Vegas and Atlantic City in the United States with an online survey restricted to members of surveysampling.com, these studies may be criticized for their limited scope. It reflects a broader concern about the potential bias and limited applicability of studies that primarily involve Western participants, as highlighted by the study by Martins et al. (2021), which predominantly examines the Destination Brand Experience of a Portuguese National Park with respondents from the same nation. This critique suggests the need for a more diverse and comprehensive approach to Destination Brand Experience research to ensure the reliability and relevance of measurement tools in a global context.

As research progressed, the intricate relationship between destination brand personality, tourism services, satisfaction, and word-of-mouth communication was explored in depth. This led to the proposition of a structural framework, validated through Structural Equation Modelling (Bhattachary & Dutta, 2016). In 2018, an encompassing perspective of tourism destinations was presented through the DBE lens, revealing its profound impact on tourist trust and loyalty, especially within the context of Indian tourist destinations (Kumar & Kaushik, 2018). The pivotal role of brand experience in nurturing enduring consumer relationships was further highlighted, with a particular emphasis on tourist satisfaction as a key determinant for global destination prominence (Singh & Mehraj, 2018).

The recent literature on DBE unveils a theoretical expansion, albeit not methodological, in understanding how DBE influences varied aspects of consumer behaviour and brand perception in the tourism realm. The study by Yu, Moon, Chua, & Han, 2024 articulates a theoretical framework that underscores the importance of DBE on brand authenticity and the consequent consumer loyalty. This line of inquiry aligns with the findings presented by Lin et al. (2023), who explore the application of a brand experience model to evaluate competitive differentiation and brand positioning in tourism. Their emphasis on the affective and sensory dimensions of DBE resonates with the arguments set forth in our work, and establishes a clear connection with the research of Kim et al. (2022), which advocates for the incorporation of heritage resources to enhance brand appeal. This multidimensional approach to DBE is further expanded upon by the study of Ngwira et al. (2023), which suggests an extension of the DBE model to include relational and spiritual dimensions, especially relevant in the post-pandemic tourist context.

Brand experiences, as delineated by Brakus et al. (2009), encompass sensory, behavioural, intellectual, and affective dimensions that influence consumer perception, behaviour, and emotions towards a brand (see extended explanation in Appendix A).

2.2. Sentiment analysis

Often referred to as opinion mining, sentiment analysis is a computational technique that uncovers and categorizes emotional tones embedded in consumers' text snippets (Liu, 2012). Its main purpose is to break down the polarity of user feedback — in other words, to determine whether a user's stance towards a particular subject, topic, or entity is positive, negative, or neutral (Pang & Lee, 2008). Sentiment analysis employs a blend of Natural Language Processing (NLP) techniques and machine learning methodologies, extracting and identifying subjective information from a dataset (Agarwal et al., 2011). There are two prominent approaches to sentiment analysis: lexicon-based and machine learning-based (Taboada et al., 2011).

The lexicon-based method leverages predefined lists of words, known as thesauri, which come with assigned polarity values, such as sentiment lexicons. This method calculates the overall polarity of a text by summing up the polarity values of its constituent words, based on the assumption that a sentence or document's sentiment directly aligns with the polarity of the words it contains (Turney, 2002; Wilson et al., 2005).

On the other hand, the machine learning-based method uses supervised or unsupervised algorithms to train models that can classify texts based on their polarity (Pang et al., 2002). Supervised techniques need a labelled dataset with known polarities for training and validating the model. In contrast, unsupervised methods do not require polarity labels, relying instead on clustering or topic detection techniques (Ramage et al., 2010). Despite their higher adaptability to specific contexts and domains, these methods can demand more computational resources and a high-quality training dataset (Liu, 2012).

3. Methodology

The widely adopted analytical methods of Partial Least Squares (PLS) and Structural Equation Modelling (SEM) have played a significant role in social science research, including studies on Destination Brand Experience (DBE). However, recent findings, as indicated by Westland (2014), have revealed that PLS projections can exhibit biases and variability, particularly when based on limited sample sizes. To mitigate these issues, large sample sizes are recommended. Furthermore, PLS may suffer from inadequate hypothesis evaluation, resulting in an excessive number of false positive outcomes.

Both SEM and PLS are confirmatory techniques grounded in pre-existing theories and models, making them susceptible to biases if the underlying theoretical model is flawed or incomplete. This reliance on theory can limit their generalizability across diverse contexts or populations, as noted by Hair et al., (2010).

In contrast, machine learning offers an exploratory approach, capable of handling varying dataset sizes without strict reliance on theoretical assumptions. Machine learning techniques can reduce biases and variability, providing a flexible and robust evaluation of data relationships. They optimize models based on data, seeking accurate data representation, and can generalize effectively to new datasets. Traditional methodological approaches in DBE research have highlighted limitations, such as limited common method bias and item bias in multi-sample tests, as seen in studies by Ngwira et al. (2023) and Boo et al. (2009). Kumar and Kaushik (2018) caution about limited samples and potential response biases in DBE research. Overall, machine learning techniques offer a promising alternative to address these challenges in DBE research.

In this article, we describe a methodology that enhances textual data analysis by leveraging machine learning. We extract features from texts and quantify them in the DBE dimensions using the thesauri constructed for this purpose. The technique goes beyond traditional analytical methods, such as simple sentiment analysis and word frequency or percentage counts. Instead of merely uncovering the extent to which a consumer likes something, the scale-oriented text analysis combines the richness of traditional textual and sentiment analysis with the theoretical structure and analytical rigour provided by conventional marketing scales. The technique we describe is novel and could potentially increase response rates and facilitate a more natural methodology for both practitioners and academics. We believe that the possible improvements in efficiency that our methodology offers justify its application.

3.1. Research design

The present study utilises online user generated content (UGC) as a data source to evaluate the DBE of the Italian city of Turin as a tourist destination, using it as a case study, although it is perfectly generalisable and extrapolatable to other cities. Specifically, the study analyses reviews related to a set of resources (cultural, transport or experiences) that will be detailed later and provide an excellent representation of the Italian city's DBE. The use of UGC as a data source for evaluating the DBE of tourist destinations has gained prominence in recent years (Buhalis & Law, 2008; Marine-Roig & Clavé, 2015). Similarly, the use of sentiment analysis as a tool for assessing destinations has been widely adopted in tourism research (Jabreel et al., 2017; Eunil et al., 2020). To carry out the sentiment analysis, an open-source platform based on Python libraries for scientific computing is employed. This allows access to functionalities for data analysis and mining, sentiment analysis, topic modelling, and classification through machine learning. Subsequently, Table 1 presents an outline of the entire methodology employed.

3.2. Data acquisition: selected data (temporal, spatial and category scope)

Firstly, the content of reviews (data) is collected from the Google Reviews platform for the years 2011 to March 2023. Google integrates Google Reviews into the Google My Business platform, allowing users to provide feedback, ratings, and opinions on various establishments, products, or services. These evaluations build a collective public rating that helps potential consumers make informed decisions based on others' experiences and perspectives and enables researchers to analyse phenomena or trends across multiple disciplines. Google Reviews not only serve as a valuable resource for understanding the local business landscape, but also play a crucial role in fostering decision-making and the development of policies related to trade or destination marketing.

Using web scraping techniques, various datasets were compiled containing a set of reviews related to the tangible and intangible elements that form an excellent example of the DBE of the city of Turin. Specifically, and after reaching a consensus, those that represented the city with greater weight (reviews) and with indisputable recognition (uniqueness) were selected and categorised into three groups. The result is summarised in Table 2.

The dataset focuses on features related to guest comments across the different categories mentioned. The main variables taken into account

Table 1
Outline of the employed methodology. Multi-analysis of the DBE.

SENTIMENT ANALYSIS	TOPIC MODELLING	MULTIPLE THESAURI	STATISTICAL ANALYSES	MACHINE LEARNING
VADER Lexical database "Valence Aware Dictionary for sEntiment Reasoning" **SentiART** (different computational SA tools) (Borg & Boldt, 2020) (Jacobs, 2019)	**Latent Dirichlet Allocation (LDA)** A technique that identifies underlying patterns (Jelodar et al., 2019)	**Roget's Thesaurus** **4 thesauri representing the 4 dimensions of the DBE** Groups semantically related words or "meaning clusters". (Jarmasz, 2012)	Hypothesis testing **Student's t-test** (Efron, 1969)	Machine Learning **algorithm** **AdaBoost** Able to classify instances based on their dimension scores and other derived features (Schapire, 2013)

Table 2
Selected elements that build the Turin's DBE.

Category	Selection	Reason	Total Registers	Total registers with reviews
Welcome/access infrastructure	Turin Airport - Caselle	The most important air access.	6402	2169
	Porta Nuova Railway Station	The main railway station of Turin and the third busiest of Italy.	6412	2183
Emblematic tourist attractions	Egyptian Museum of Turin	The second most important for its collection of Egyptian antiquities in the world, after the Egyptian Museum in Cairo.	43,320	20,990
	Mole Antonelliana - National Museum of Cinema	The symbol of the city.	41,803	17,423
	Royal Palace	The first and most important of the Residences of the Royal House of Savoy.	5553	2210
Genuine and local experiences	Shroud of Turin in the Cathedral of St John the Baptist	It is believed by many to be the real burial cloth of Jesus Christ	4766	1645
	Tasting of Bicerin (Historical coffee shop)	The traditional and native drink of Turin	2289	1419
	Tasting Gianduja (Artisan chocolate maker)	A unique an universally known chocolate originary from Turin.	1835	852
		Total	112,380	48,891

were: the number of comments, the date, and the comments (already automatically translated into English upon download to allow for content universality). Additionally, depending on the dataset, two new variables were created: gender (using an Application Programming Interface -API- to predict the gender of a name) and the original language of the comment (using the function in Google Sheets that detects the language of a given text string).

- The "gender" variable in the database represents the estimated gender of the visitor who wrote the review, obtained through the genderize.io API (https://genderize.io/). The inclusion of this information allows researchers to explore possible relationships between the guests' gender and their experiences, preferences, or perceptions of tourist attractions. Moreover, it enables more accurate comparative studies on the differences in the various dimensions of the DBE.
- The "language" variable indicates the original language of the visitor's review. Knowing the distribution of languages in the reviews can provide relevant information about the diversity of the visitor population and assist in designing strategies to adapt communication and marketing efforts to different linguistic and cultural backgrounds.

3.3. Text pre-processing and cleaning

The study processed data using basic Natural Language Processing (NLP) techniques. The overall sentiment analysis process consists of a series of sequential steps. Firstly, a cleaning and normalisation process began with the extraction of data (text reviews) from the Google collaborative platform. To do this, all languages used were detected, and an automatic translation of all content to the majority language, English, was carried out to achieve uniformity in the treatment of the reviews in order to make a fair comparison.

Secondly, we segmented the text into sentences and tokens. Tokenisation involves dividing the text into units, such as words and punctuation marks. Thirdly, the analysis carried out part-of-speech tagging (PoS tagging), which identifies the grammatical form (morphosyntactic category) of words based on the definition of each word in context. For example, in the sentence "the restaurant is great", "restaurant" is a noun, and "great" is an adjective.

Fourthly, the analysis performed lemmatisation, which converts each word to its root form and transforms the opinions to lowercase. Lemmatisation aims to reduce the word to its lemma, i.e., the root form, canonical form, or the most common form of words. For example, "runs", "running", and "ran" are all forms of the word "run".

Lastly, the study included a list of stop words, such as "the", "and", or "other", which distort the meaning of sentiment analysis, topic modelling, and the subsequent textual analysis.

3.4. Topic modelling

The study employed Latent Dirichlet Allocation (LDA) to perform Topic Modelling. LDA is a topic modelling technique that identifies underlying patterns of words and themes within a set of documents (Jelodar et al., 2019). LDA is a generative probabilistic model that assumes each document is a mixture of various topics, and that each topic is composed of a collection of words with different probabilities. The algorithm utilises Dirichlet distributions to model both the distribution of topics in documents and the distribution of words in each topic. By applying LDA, we obtained a compact and coherent representation of the themes present in a corpus, facilitating the understanding and analysis of large volumes of text.

3.5. Sentiment analysis, data mining and machine learning

The study employed a sentiment analysis tool, model, and lexical database called "Valence Aware Dictionary for sEntiment Reasoning" (VADER) (Borg & Boldt, 2020), which is rule-based and perfectly optimised for analysing the sentiments of UGC. Through this tool, each word in the lexicon (in English or translated into English) is automatically classified as positive, neutral, or negative, and it not only displays the assigned scores but also the degree to which a sentiment is positive or negative (Hutto & Gilbert, 2014). VADER is essentially constructed from well-established sentiment lexicons that use lexical attributes typically employed to express sentiment in social media. The VADER lexicon contains over 7500 words, including abbreviations, acronyms, initials, and icons. It also utilises sentiment modules from NLTK (Natural Language Toolkit) and is complemented by the Data Science Lab. Specifically, VADER calculates the sentiments of each comment and returns them with a score ranging from −1 for negative sentiment to 1 for positive sentiment. It is currently considered a valuable standard in social media lexicons (Bonta & Janardhan, 2019). In addition to VADER, SentiART is also employed, a multivariable SAT (different computational SA tools) capable of calculating four lexical features (arousal, emotion potential, valence, and aesthetic potential) and two inter-lexical features (valence span and arousal span) with the aim of predicting various aspects associated with the sentiment distribution of a text (Jacobs, 2019).

The analysis converted textual data into numerical features to be treated with various statistical and machine learning methods, primarily boxplots, hypothesis tests, and classification algorithms. The conversion of sentiments (dimensions) to numerical scores allowed for visualising the distribution of sentiment scores among different categories or groups, and the Student's t-test was employed to determine whether there were significant differences between the sentiment scores of different groups. Finally, machine learning algorithms, such as AdaBoost, were applied to classify instances based on their dimension scores and other derived features.

3.6. Thesaurus

We designed a comprehensive and appropriate thesaurus of terms with multiple synonyms representing the four dimensions of Brakus et al.'s (2009) Brand Experience (BE) as a novel, differentiating, and relevant contribution. This process was carried out using the online version of the Encyclopaedia Britannica, considered one of the best in English (Hamilton, 2003), and the Oxford Thesaurus of English. The study consulted Roget's Thesaurus to locate additional synonyms in order to further improve the thesaurus before incorporating it into the analysis software. It consists of six main categories, represented as a tree with over a thousand branches, each of which groups semantically related words or "meaning clusters". Although the words included in Roget's Thesaurus are not necessarily exact synonyms, they can be considered as nuances or variations of a meaning or as a range of related concepts. Roget's thesaurus has proven to be an excellent resource for measuring semantic similarity; lexical chains are easily built but more difficult to evaluate (Jarmasz, 2012). This process helped us develop a final list of words that were distributed relatively evenly across the four original dimensions of Brakus et al.'s (2009) BE.

Based on the different thesauri, the programme identifies relevant reviews and assigns them a weight in the dimension of the construct. For example, Table 3 shows some words collected in each dimension, and Table 4 provides an example of the reviews.

4. Results

4.1. Topic modelling

Through the application of Latent Dirichlet Allocation (LDA) for topic modelling of various cultural, experiential, and transport elements in the city of Turin, several main thematic areas have been identified for each element, with associated keywords highlighting the key aspects of the respective themes (see Table 5). For example, the Mole Antonelliana is characterised by themes including its iconic status (symbol, history, museum, representation, recognisable), positive experiences (panoramic, view, beautiful, top, cinema, interesting), and negative experiences (expensive, worthless, queue, overpriced). In contrast, the topics of the Egyptian Museum consist of valuable experiences (interesting, complete, experience, beautiful, Egyptian, worth, treasures) and uncomfortable feelings (shame, shameless, shameful, colonist, scandal, stolen). The versatility of the LDA method has allowed for the generation of meaningful insights by synthesising thousands of data points, facilitating a more comprehensive understanding of visitors' experiences and perceptions of the elements that shape the Destination Brand Experience of the city of Turin.

4.2. Evolution of sentiments: Shroud of Turin

Upon employing the sentiment analysis tool, model, and lexical database of "Valence Aware Dictionary for sEntiment Reasoning" (VADER) (Borg & Boldt, 2020) and the SentiART, a multivariable SAT (different computational SA tools) for calculating lexical and inter-lexical features (Jacobs, 2019) on the various items studied, an example of the results for the evolution of sentiments on visiting the Shroud of Turin between 2016 and 2023 is presented in Fig. 1. It is essential to consider both the overall sentiment and the various

Table 3
Example of words included in the thesaurus representing each dimension.

Affective	Behavioural	Sensory	Intellectual
Beautiful	Learn	Absorbed	Adventurous
Unique	Distrust	Acidic	Aesthetic
Adorable	Behaviour	Acoustic	Functional
Ugly	Conduct	Delicious	Analytical

Table 4
Examples of reviews representing each dimension.

Dimension	Item	Review
Affective	Mole Antonelliana	Also *beautiful* seen from below, then from above!
Behavioural	Egyptian Museum	You can *learn*, that is not little.
Sensory	Gianduja	It was *delicious*!
Intellectual	Turin Airport (Caselle)	Very *functional*!

Table 5
Topic Modelling following the LDA method.

	Items	Topics	Topics Keywords
Cultural	Mole Antonelliana	Icon	*symbol, history, museum, representation, recognisable*
		Positive experience	*panoramic, view, beautiful, top, cinema, interesting*
		Negative experience	*expensive, worthless, queue, worthless, overpriced*
	Egyptian Museum	Valuable	*interesting, complete, experience, beautiful, Egyptian, value, treasures*
		Uncomfortable feelings	*shame, shameless, shameful, colonist, scandal, stolen*
	Royal Palace	Specific features	*savoy, history, beautiful, palazzo, royal, gardens, armory*
Experience	Shroud of Turin	Specific features	*holy, saint, ancient, chapel, shroud, cathedral, church*
	Bicerin	Specific features	*chocolate, drink, coffee, cream, small, hot, milk*
		Icon	*worth, historic, typical*
	Gianduja	Specific features	*chocolate, quality, cocoa, cream, shop, bitter*
		Positive experience	*tasting, experience, great, delicious, excellent*
Transport	Turin Airport (Caselle)	Specific features	*small, queue, staff, check, waiting, control, parking, clean*
	Train Station Porta Nuova	Specific features	*beautiful, clean, nice, station, train, shops, tracks, city*

emotional components in order to gain a comprehensive understanding of Turin's Destination Brand Experience (DBE), particularly in regard to the Shroud of Turin as a unique tourist attraction.

In this case, the data demonstrate an overall increase in positive sentiment, with a peak in 2020, alongside relatively stable negative sentiment. This suggests that visitors have generally had a predominantly positive experience with the attraction in the destination. An analysis of the emotional components indicates that "happiness" has experienced a steady increase, reaching a maximum in 2021, while other emotions such as anger, fear, and disgust have shown a downward trend. The increase in positive sentiment and happiness could contribute to enhancing Turin's DBE, as positive emotions are likely to encourage repeat visits and generate positive word-of-mouth. In addition to the main sentiment components, it is worth noting the changes in other emotions such as sadness and surprise. Sadness has remained relatively stable and has gradually increased over the years, while surprise displays fluctuations without a clear trend. These emotions could be associated with the spiritual and historical significance of the Shroud of Turin, which elicits complex emotions in visitors.

4.3. Statistical analysis through hypothesis testing of the distributions of the DBE

Table 6 displays the most significant comparisons made across the dimensions of DBE and the three main categories: Culture, Experience, and Transport. It can be observed that the Student's t-test values do not always indicate insignificance.

Among all the combinations shown, it is worth noting that the sentiments of the sensory dimension in the two main access points of Turin had a *t*-test result of 0.797, with a p-value of 0.425 and a sample size of N = 4351. As the p-value (0.425) is greater than the typical threshold for statistical significance of 0.05, it indicates that we cannot reject the null hypothesis and cannot claim that there are statistically significant differences in the sensory dimension between the airport and the train station in Turin.

However, as a contrasting example, when evaluating the differences in affective perceptions between the Egyptian Museum and the Mole Antonelliana, the *t*-test result was 5.511, with a p-value of 0.000 and a sample size of N = 35,488. Unlike the previous case, the p-value (0.000) is less than the typical threshold for statistical significance of 0.05, indicating that we can reject the null hypothesis and assert that there are statistically significant differences in the affective dimension between the Egyptian Museum and the Mole Antonelliana (see Fig. 2).

However, the distributions of the sensory dimension for the Royal Palace and the Egyptian Museum show similar means. After applying the Student's t-test to compare these two distributions, a t-value of 0.396 and a p-value of 0.692 were obtained, with a sample size of N = 21,734. This suggests that we cannot reject the null hypothesis and assert that there are statistically significant differences between the means of both distributions. Therefore, it can be concluded that visitors' sensory perceptions concerning the Royal Palace and the Egyptian Museum are comparable and do not present relevant differences in terms of the sensory experience.

On the other hand, from Table 7 of disaggregated emotions, it can be inferred that several distributions among the various items are similar. For example, in the "happiness" sentiment of the experience group, it is concluded that the perceptions of "happiness" concerning the Shroud of Turin and the Gianduja are similar and do not present notable differences in terms of the emotion experienced by individuals in these contexts. In other words, visiting the Shroud of Turin does not involve a different "happiness" than tasting the traditional Bicerin drink.

Table 8 displays the comparisons between the items and opinions originating from Western and Eastern language/culture groups. For example, a statistically significant difference is observed in the affective dimension of the Shroud of Turin between Eastern (M = 10.9352, SD = 13.8858) and Western (M = 16.9009, SD = 25.0957) cultures; t(19260) = 4.659, $p < 0.001$. The differences found in the affective dimension could be attributed to various factors, such as cultural differences or disparities in value and belief systems (Hofstede, 1980), which may play a significant role in the affective perception of the Shroud of Turin. Furthermore, religious differences and exposure to religious education could also influence the affective perception of this relic (Tsai, 2007).

Similarly, differences are displayed in the intellectual dimension of the Egyptian Museum between Eastern and Western language/culture groups. The long-standing tradition of visiting historical heritage and hosting significant heritage museums in Western culture could influence the expectations and perceptions of Western visitors, who might value the intellectual experience in museums like the Egyptian Museum more highly (Lowenthal, 1998).

Secondly, differences in exposure and familiarity with Egyptian history and art due to education and exposure in Western-origin culture could increase interest and intellectual connection with the content of

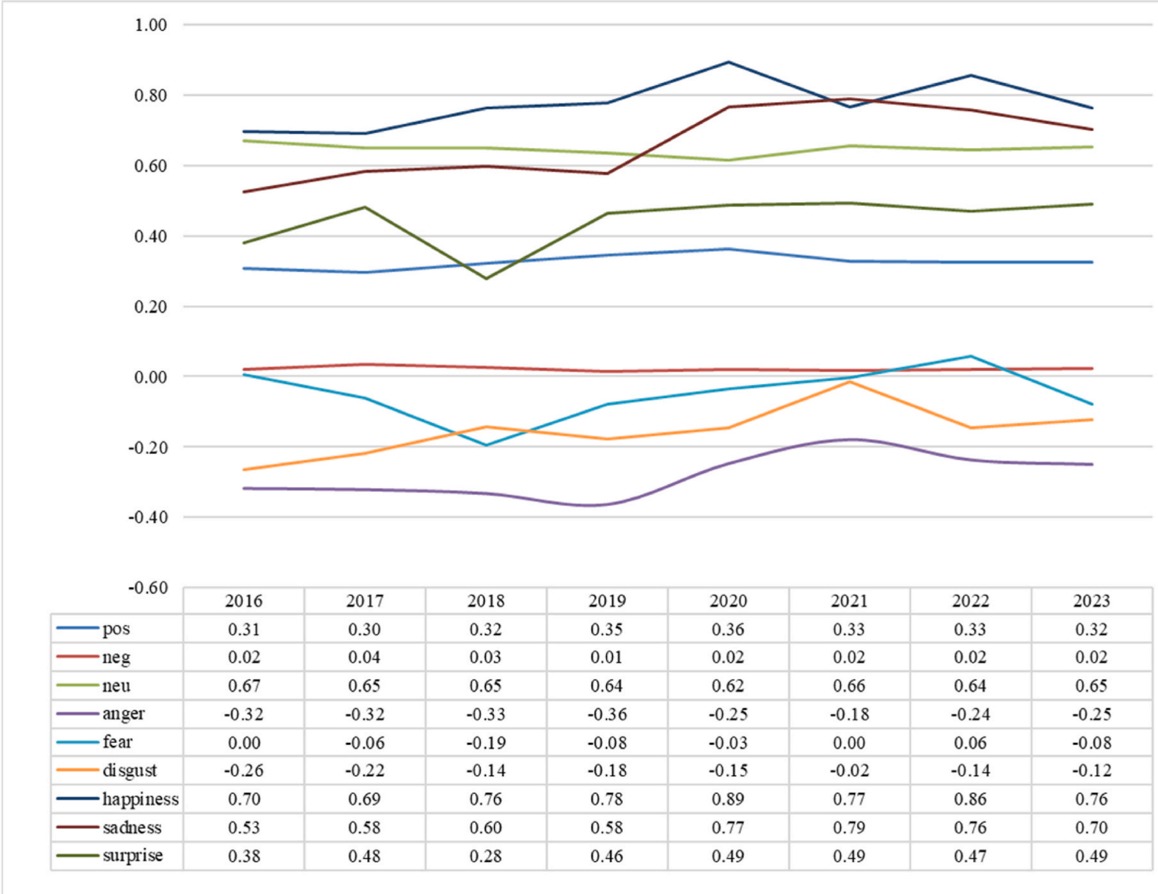

Fig. 1. Evolution of sentiments on visiting the Shroud of Turin.

Table 6
Comparative analysis between the dimensions of the DBE and the items of the city of Turin.

		BRAND EXPERIENCE DIMENSIONS			
	ITEMS SELECTED	AFFECTIVE	BEHAVIOURAL	INTELLECTUAL	SENSORY
C - C	Egyptian Museum – Mole Antonelliana	p=0.000, N=35488	p=0.000, N=35488	p=0.004, N=35488	p=0.000, N=35488
C - C	Egyptian Museum – Royal Palace	p=0.000, N=21734	p=0.000, N=21734	p=0.001, N=21734	p=0.692, N=21734*
C - C	Mole Antonelliana – Royal Palace	p=0.000, N=18698	p=0.066, N=18698*	p=0.056, N=18698*	p=0.000, N=18698
C - T	Cultural – Experience	p=0.000, N=8340	p=0.000, N=41949	p=0.000, N=41949	p=0.000, N=41949
E - E	Shroud of Turin – Bicerin	p=0.000, N=3063	p=0.000, N=3063	p=0.000, N=3063	p=0.000, N=3063
E - E	Shroud of Turin – Gianduja	p=0.000, N=2571	p=0.000, N=2571	p=0.692, N=2344*	p=0.000, N=2571
E - E	Bicerin – Gianduja	p=0.152, N=2344*	p=0.413, N=2344*	p=0.692, N=2344*	p=0.000, N=2344
E - T	Experience – Transport	p=0.000, N=8340	p=0.000, N=8340	p=0.000, N=8340	p=0.000, N=8340
T - T	Turin Airport (Caselle) – Train Station Porta Nuova	p=0.000, N=4351	p=0.000, N=4351	p=0.000, N=4351	p=0.425, N=4351*
T - C	Transport – Cultural	p=0.000, N=42311	p=0.000, N=42311	p=0.000, N=42311	p=0.000, N=42311

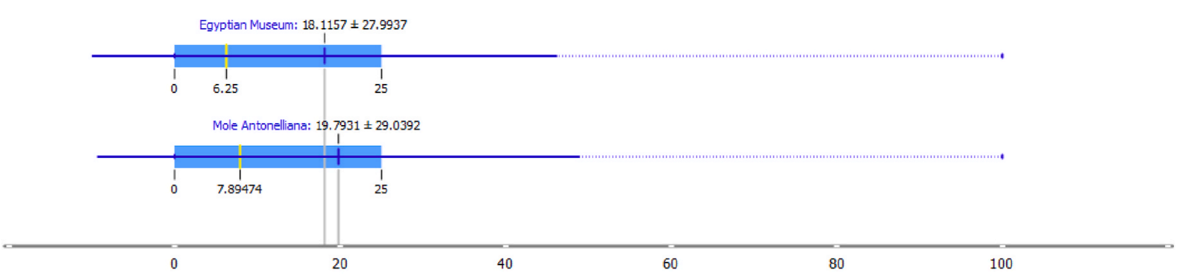

Fig. 2. Comparison of the affective dimension between the Egyptian Museum and the Mole Antonelliana in Turin.

Table 7
Comparative analysis between disaggregated emotions.

EMOTIONS DISAGGREGATED							
	ITEMS SELECTED	ANGER	SADNESS	HAPPINESS	SURPRISE	DISGUST	FEAR
C - C	Egyptian Museum – Mole Antonelliana	p=0.499, N=35488*	p=0.000, N=35488	p=0.000, N=35488	p=0.000, N=35488	p=0.000, N=35488	p=0.000, N=35488
C - C	Egyptian Museum – Royal Palace	p=0.052, N=21734*	p=0.703, N=21734*	p=0.000, N=21734	p=0.538, N=21734*	p=0.000, N=21734	p=0.000, N=21734
C - C	Mole Antonelliana – Royal Palace	p=0.023, N=18698	p=0.000, N=18698	p=0.000, N=18698	p=0.000, N=18698	p=0.004, N=18698	p=0.000, N=18698
C - E	Cultural – Experience	p=0.000, N=8340	p=0.000, N=8340	p=0.000, N=8340	p=0.000, N=8340	p=0.000, N=8340	p=0.000, N=8340
E - E	Shroud of Turin – Bicerin	p=0.000, N=3063	p=0.000, N=3063	p=0.189, N=3063*	p=0.000, N=3063	p=0.000, N=3063	p=0.000, N=3063
E - E	Shroud of Turin - Gianduja	p=0.000, N=2571	p=0.000, N=2571	p=0.214, N=2571*	p=0.000, N=2571	p=0.000, N=2571	p=0.000, N=2571
E - E	Bicerin – Gianduja	p=0.152, N=2344	p=0.000, N=2344	p=0.019, N=2344	p=0.000, N=2344	p=0.000, N=2344	p=0.401, N=2344*
E - T	Experience – Transport	p=0.000, N=8340	p=0.000, N=8340	p=0.000, N=8340	p=0.000, N=8340	p=0.000, N=8340	p=0.000, N=8340
T- T	Turin Airport (Caselle) – Train Station Porta Nuova	p=0.000, N=4351	p=0.007, N=4351	p=0.001, N=4351	p=0.036, N=4351	p=0.000, N=4351	p=0.000, N=4351
T - T	Transport – Cultural	p=0.007, N=42311	p=0.007, N=42311	p=0.000, N=42311	p=0.000, N=42311	p=0.692, N=42311*	p=0.004, N=42311

Table 8
Cultural differences: Western – Eastern.

	GR.	ITEMS	AFFECTIVE	BEHAVIOURAL	INTELLECTUAL	SENSORY
CULTURAL DIFFERENCES Western – Eastern**	C	Mole Antonelliana	p=0.000, N=16226*	p=0.278, N=16226	p=0.000, N=16226*	p=0.000, N=16226*
	C	Egyptian Museum	p=0.000, N=19262*	p=0.000, N=19262*	p=0.000, N=19262*	p=0.196, N=19262
	C	Royal Palace	p=0.849, N=2472	p=0.000, N=2472*	p=0.582, N=2472	p=0.429, N=2472
	E	Shroud of Turin	p=0.033, N=1645*	p=0.727, N=1645	p=0.306, N=1645	p=0.000, N=1645*
	E	Bicerin	p=0.501, N=1418	p=0.630, N=1418	p=0.902, N=926	p=0.449, N=1418
	E	Gianduja	p=0.226, N=926	p=0.896, N=926	p=0.902, N=926	p=0.111, N=926
	T	Turin Airport (Caselle)	p=0.000, N=2168*	p=0.744, N=2168	p=0.000, N=2168*	p=0.308, N=2168
	T	Train Station Porta Nuova	p=0.000, N=2183*	p=0.793, N=2183	p=0.917, N=2183	p=0.357, N=2183

Table 9
Comparative analysis between genders.

	ITEM	GENDER	AFFECTIVE	BEHAVIOURAL	INTELLECTUAL	SENSORY
C	Mole Antonelliana	M – F	p=0.000, N=15671*	p=0.964, N=15671	p=0.063, N=15671	p=0.527, N=15671
C	Egyptian Museum	M – F	p=0.000, N=18633*	p=0.428, N=18633	p=0.000, N=18633*	p=0.505, N=18633
C	Royal Palace	M – F	p=0.025, N=2372*	p=0.691, N=2372	p=0.024, N=2372*	p=0.693, N=2372
E	Shroud of Turin	M – F	p=0.008, N=1556*	p=0.791, N=1556	p=0.622, N=1556	p=0.308, N=1556
E	Gianduja	M – F	p=0.682, N=903	p=0.999, N=903	p=0.847, N=903	p=0.075, N=903
E	Bicerin	M – F	p=0.120, N=1354	p=0.707, N=1354	p=0.931, N=1354	p=0.605, N=1354
T	Turin Airport Caselle)	M – F	p=0.169, N=2088	p=0.532, N=2088	p=0.674, N=2088	p=0.487, N=2088
T	Train Station Porta Nuova	M – F	p=0.693, N=2109	p=0.209, N=2109	p=0.276, N=2109	p=0.155, N=2109

the Egyptian Museum (Falk & Dierking, 2000). Finally, the differences in cognitive and thinking styles between Eastern and Western cultures (Nisbett et al., 2001), such as the analytical thinking centred on specific objects and categories in Westerners and the holistic thinking that considers context and relationships in Easterners (Nisbett & Masuda, 2003), could affect the way both cultures experience the Egyptian Museum and its content.

Table 9 displays the comparison for the gender variable. All elements within the cultural group (Mole Antonelliana, Egyptian Museum, and Royal Palace) present significant differences between female and male genders in the affective variable. For instance, in the Mole Antonelliana, significant differences are observed in the mean scores and variability. The female gender tends to experience more intense or varied emotions compared to men, which could lead to a higher mean score and variability in the affective dimension (Fisher & Dubé, 2005). These differences could be due to cultural, social, or biological factors that influence how men and women experience and express their emotions (Brody & Hall, 2000). Furthermore, differences in gender socialisation may affect expectations and emotional experiences concerning the Mole Antonelliana and other aspects of the destination brand experience (Kimmel, 2000).

Fig. 3 presents the percentage distribution of the DBE dimensions (affective, behavioural, intellectual, and sensory) among all resources that make up the city of Turin's DBE. In the case of the affective dimension, the Shroud of Turin (34.35%) and the Royal Palace (33.75%) exhibit the highest percentages, suggesting an intense emotional connection at these historical and cultural sites. This is consistent with the research of Bagozzi et al. (1999), which argues that emotional

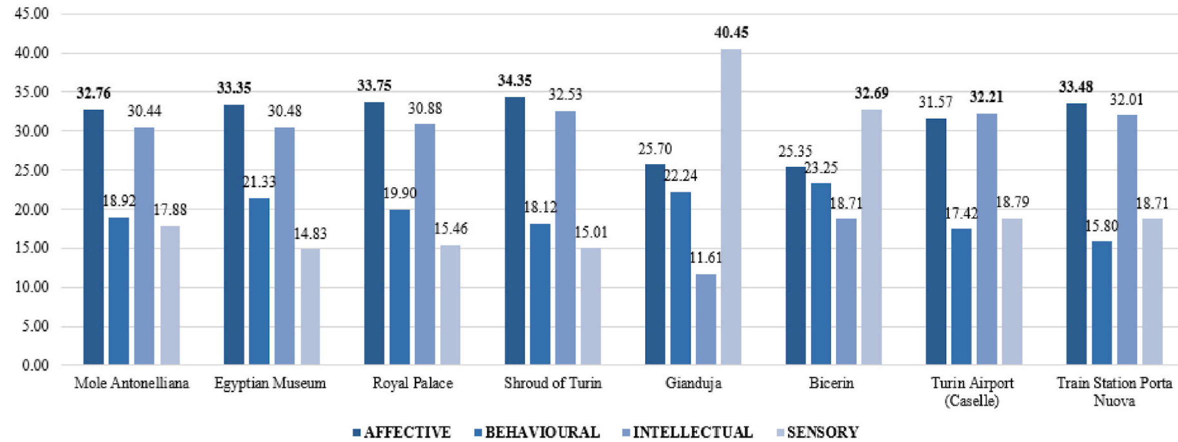

Fig. 3. Percentage distribution of the DBE dimensions among the analysed items.

experiences have a significant impact on the formation of consumer attitudes and behaviours.

Regarding the behavioural dimension, Bicerin (23.25%) displays the highest percentage, suggesting that tourists may be more inclined to share and discuss their experience with this typical Turin product. In contrast, the Train Station Porta Nuova (15.80%) might not generate significant behaviour among tourists, as train stations are often seen as transit points rather than destinations in themselves (Lyons & Chatterjee, 2008).

The intellectual dimension is found in the Shroud of Turin (32.53%). This is consistent with the literature on information processing (Keller, 1993; Petty & Cacioppo, 1986), which suggests that advertising and brand communications can influence consumer beliefs and expectations. The Shroud of Turin is an object laden with history and religious significance, which may increase intellectual interest in visiting it.

Lastly, in relation to the sensory dimension, we note that sensory stimuli can evoke emotions and memories (Hultén et al., 2009a, 2009b, pp. 1–23) and are essential for creating memorable experiences (Krishna, 2012; Lindstrom, 2005). In this regard, Fig. 4 shows a comparison between the Egyptian Museum and Gianduja specifically. It is observed that Gianduja (40.45%) exhibits the highest percentage in the sensory dimension, suggesting a high sensory experience when tasting this typical Italian chocolate. On the other hand, the Egyptian Museum (14.83%) may offer a more limited sensory experience. This may be related to the fact that the sensory experience in a museum tends to be low, compared to places involving more varied stimuli, such as flavours, smells, and sounds (Spence et al., 2014).

4.4. Classification by machine learning techniques

By using a classifier, the aim is to determine the extent to which the use of features (DBE dimensions) derived from the text allows distinguishing between classes using a machine learning algorithm. The higher the performance achieved in distinguishing one class, the better the selected features will define that class, meaning it will be more distinct from other classes. Likewise, the classes have been balanced to avoid bias. Following a classic classification process, we have trained and validated an Ada Boost algorithm through an iterative cross-validation process to distinguish a class. Machine learning classification employs cross-validation as a technique to evaluate a model's

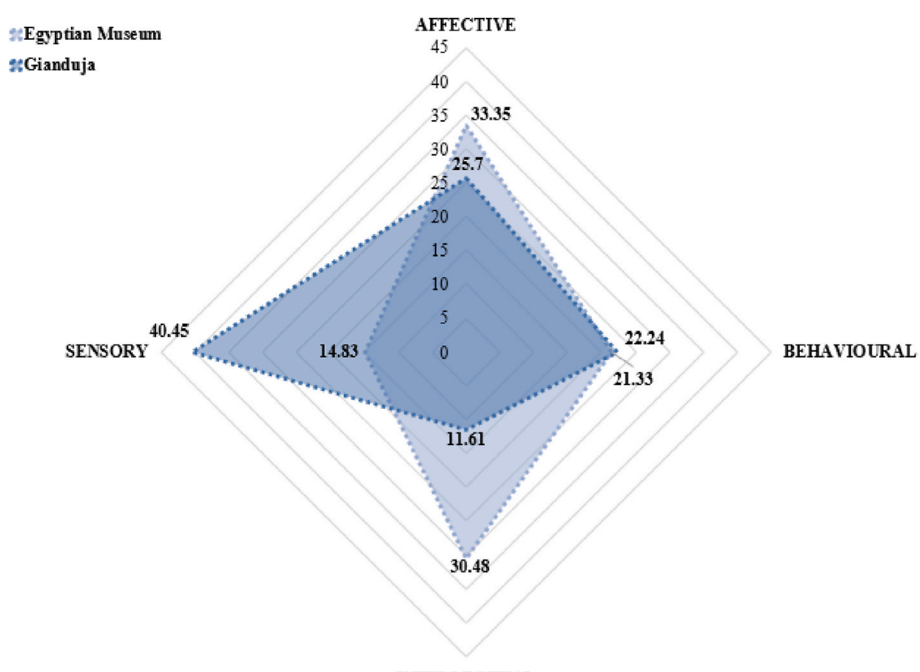

Fig. 4. Percentage distribution of the DBE dimensions between the Egyptian Museum and Gianduja.

performance, dividing the dataset into multiple subsets. In our approach, we divide the data into five equally sized folds. Four of these folds serve as training data, while we reserve the remaining fold for testing. We repeat this process five times, with each fold taking its turn as the test set once. After completing the five trials, we average the model's performance to give a more reliable and accurate estimate of how well it will generalize to unseen data. To maximise performance, we have also carried out parameter optimisation (hypertuning).

The model's ability to reduce classification errors, including both false positives and false negatives, adds to the validity and robustness of the conclusions we draw from the data. The following findings indicate that the AdaBoost classification approach is an effective tool for addressing similar classification problems in future research.

Looking at the confusion matrix (see Table 10), we see that the performance varies among different classes. The matrix shows numerous accurate classifications but also reveals some confusion within specific classes. For the airport, the model correctly predicts 56.5% of cases, although it confuses it with the Egyptian Museum (21.2%) and the Mole Antonelliana (14.0%). On the other hand, in the case of Bicerin, the model achieves correct classification 75.2% of the time, with the Egyptian Museum being the class with which it is most confused (12.8%). The model demonstrates good performance in predicting the Egyptian Museum with an accuracy of 85.0%, Mole Antonelliana with 82.1%, Royal Palace with 73.7% accuracy, and Shroud of Turin with 71.8%. Regarding transportation, the model classifies Train Station Porta Nuova with 59.6% of cases, but exhibits confusion with Turin Airport (Caselle).

Various metrics are applied to measure the relevance of features in the classification process (see Table 11). The affective dimension has the highest information gain (Info. Gain) and the highest gain ratio, suggesting that this feature provides the most information about the target variable and would be the best predictor among the four dimensions analysed. Additionally, it also presents the highest χ^2 value, indicating a greater dependency on the target variable. The sensory dimension, on the other hand, has the highest values in ANOVA and ReliefF. The ANOVA test implies that there is a statistically significant difference between the group means based on the sensory dimension, while ReliefF suggests that this feature could be useful in differentiating between classes.

However, the behavioural dimension and the intellectual dimension appear to be less relevant in the classification of attractions according to the presented metrics, as their values are generally lower compared to the previous dimensions.

The strong performance of the AdaBoost model in classifying classes, through features extracted from the dimensions of thesauri based on user reviews, indicates that our methodology has successfully extracted relevant features that characterise and synthesise people's opinions and feelings.

5. Conclusions and discussion

5.1. Theoretical implications

Multidimensional Methodology and Advanced Analytical Techniques: This study marks a seminal contribution to academic discourse on DBE, introducing a profound, contextualized understanding through an advanced, multidimensional methodology. Leveraging a vast array of real-world data generated by visitors, it transcends conventional techniques by integrating five types of analysis: sentiment analysis, topic modelling, multi-thesaurus analysis, statistical analyses through hypothesis testing, and machine learning-based classification. The flexible Latent Dirichlet Allocation approach and tools like VADER and SentiART enhance the understanding of DBE, offering robust means for analysing visitor reviews and identifying key thematic areas. This multifaceted approach provides a holistic view of DBE, setting a new benchmark for future research.

Novel Measurement Tools: The development of a unique set of thesauri to measure a city's DBE through User Generated Content represents a novel method for quantifying the original dimensions of the Brand Experience by Brakus et al. (2009) within visitor comments. This new way of measuring the DBE of cities proposes a clear representation and weight of sensory, behavioural, intellectual, and affective dimensions, offering versatile tools for future research and methodology.

Our research marks a transformative shift in DBE studies, both theoretically and methodologically. We introduce a model that recognizes intricate DBE differences, offering actionable insights for destination marketers. Methodologically, our work pioneers a multifaceted approach, combining advanced textual analysis with machine learning. This methodology provides a holistic view of DBE, integrating sentiment analysis and key theme identification.

5.2. Managerial implications

Destination Management Strategy: Findings reveal significant differences in the affective dimension between emblematic elements of the city, such as the Egyptian Museum and the Mole Antonelliana, suggesting the need for destination managers to rethink strategies to shape a renewed DBE. This involves understanding and enhancing the sensory experiences at key access points, acknowledging that the sensory experience at both access points is similar, which may influence the

Table 10
Confusion Matrix.

		Predicted							
		Airport	Bicerin	Egyptian Museum	Gianduja	Mole Antonelliana	Royal Palace	Shroud of Turin	Train Station Porta Nuova
Actual	Airport	**56.50%**	0.80%	21.20%	1.00%	14.00%	1.90%	2.00%	2.70%
	Bicerin	5.30%	**75.20%**	12.80%	0.40%	5.30%	0.40%	0.00%	0.40%
	Egyptian Museum	4.00%	0.20%	**85.00%**	0.10%	8.80%	0.90%	0.70%	0.30%
	Gianduja	8.90%	0.00%	5.20%	**72.60%**	10.40%	1.50%	0.00%	1.50%
	Mole Antonelliana	4.40%	0.20%	11.00%	0.70%	**82.10%**	0.50%	0.70%	0.50%
	Royal Palace	4.10%	0.30%	14.00%	0.00%	6.60%	**73.70%**	0.80%	0.40%
	Shroud of Turin	3.50%	0.00%	10.00%	0.00%	13.50%	0.80%	**71.80%**	0.40%
	Train Station Porta Nuova	12.30%	0.90%	11.10%	0.30%	10.80%	0.60%	4.20%	**59.60%**

Table 11
Feature importance.

Dimension	Info. gain	Gain ratio	Gini	ANOVA	χ^2	ReliefF	FCBF
Behavioural	0.043	0.029	0.010	33.619	507.933	0.010	0.00000234
Affective	0.089	0.052	0.019	54.714	992.753	0.017	0.0468
Intellectual	0.029	0.023	0.006	18.867	393.024	0.012	0.00000164
Sensory	0.076	0.038	0.018	74.161	574.920	0.018	0.00000368

overall image tourists have of Turin. Managers should analyse this data in detail and seek specific areas for improvement, such as cleanliness, aesthetics, signage, and lighting.

Application of Machine Learning: The implementation of a machine learning model to classify reviews demonstrates how technology can assist in monitoring DBE dimensions and automating the classification of new opinions. The model's use of cross-validation ensures its robustness, enhancing the monitoring of DBE dimensions and offering destination managers a tool to design experiences that resonate with diverse tourist demographics.

Insights for Tourism Professionals: The model's commendable performance, especially in predicting landmarks, provides invaluable insights for tourism professionals. These insights can guide improvements in areas influencing visitors' sensory perceptions and help in designing tailored destination management strategies based on nuanced DBE differences discerned by the model.

5.3. Social implications

Cultural Understanding and Gender Differences in Perception: The study underscores how cultural and language differences impact the perception of destinations, highlighting the need for inclusive and sensitive marketing strategies. It reveals that women tend to experience more intense emotions than men, which might influence the affective dimension of perception. These findings have social implications for understanding gender-specific preferences and designing emotionally engaging experiences for all visitors.

Impact of Global Events: The observed increase in positive sentiment towards the Turin Shroud during the pandemic year 2020 suggests that global events can significantly influence destination perception. This has broader social implications for how destinations might respond and adapt to changing circumstances and visitor needs.

This transformative research on DBE in the city of Turin offers a comprehensive, multidimensional approach that integrates advanced textual analysis with machine learning, providing theoretical, managerial, and social insights. The study's methodological innovations and practical applications set a new precedent for understanding and enhancing the brand experience, guiding future research and destination management strategies. It recognizes intricate DBE differences and provides actionable insights for destination marketers, paving the way for tailored experiences that resonate with diverse tourist demographics and respond to the evolving global landscape.

6. Limitations and future lines of work

Machine learning and data mining have revolutionised numerous fields, including tourism. However, they present certain limitations, more due to the nature of the data than its processing, which must be taken into account, especially in research endeavours seeking methodological innovation, such as the study at hand. Machine learning algorithms largely depend on the quality and quantity of the data with which they are trained. If the data are incomplete, the model's performance can be compromised (Reddy et al., 2020). Within the context of this study, it was imperative to have analysed the dataset to ensure that all visitor opinions were accounted for and to extract certain records that contained solely emojis and not words.

There might potentially be limitations in some of the following aspects, albeit without clear evidence. Firstly, the study employed only one classifier for sentiment analysis for the sake of simplicity. While this classifier may have its merits, there exists a plethora of other techniques in the realm of machine learning and natural language processing that could potentially offer different insights or improved accuracy. Techniques such as Support Vector Machines (SVM), Random Forests, and Neural Networks have been widely recognized in the literature for their efficacy in sentiment analysis tasks. By relying on a single classifier, the study assumes a similar performance with other classification methods.

Secondly, the selection of sentiment features is another area of potential limitation. Different feature extraction methods can lead to varied results. The choice of one over the other can lead to slightly different results and potentially somewhat different rankings depending on the consistency of the data used; however, in any case, the overall final result will generally be similar.

Regrettably, we are constrained by the nature of the available data. Additionally, the use of a dataset from a specific time period can introduce temporal biases. Sentiments and their expressions evolve over time, influenced by cultural, social, and technological changes. By focusing on a specific time frame, the study might not capture the temporal evolution of sentiments, which could be crucial for understanding long-term trends and shifts in public opinion.

Looking ahead, future research directions present exciting opportunities. One promising avenue is the incorporation of additional variables into the dataset. Variables such as age, type of trip (business vs. leisure), purpose of travel (tourism, work, migration), or income level can introduce new dimensions to the analysis. For instance, understanding how sentiments vary across different age groups or income levels can provide deeper insights into the socio-economic factors influencing public opinion. Such granularity can be invaluable for policymakers, businesses, and other stakeholders aiming to tailor their strategies or interventions based on specific demographic or economic segments.

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CRediT authorship contribution statement

Víctor Calderón-Fajardo: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Rafael Anaya-Sánchez:** Investigation, Writing – review & editing. **Sebastian Molinillo:** Funding acquisition, Project administration, Resources, Supervision, Writing – review & editing.

Declaration of competing interest

The authors have no relevant financial or non-financial interests to disclose.

Appendix A

The sensory dimension of brand experiences, as defined by Brakus et al. (2009), centres around the consumers' perception and processing of information via their senses. This dimension plays a pivotal role in crafting unforgettable and meaningful experiences, as sensory stimuli hold the potential to provoke emotions and recall memories (Hultén et al., 2009a, 2009b, pp. 1–23). Existing research underscores that the strategic integration of sensory stimuli in marketing efforts can enrich brand perception and fortify emotional bonds with consumers (Krishna, 2012; Li, Lin, & Xiao, 2022; Lindstrom, 2005). For example, background music, scents, and lighting in a retail setting can shape customers' mood and purchasing patterns (Spence et al., 2014).

The behavioural dimension concentrates on the impact of brand experiences on consumer behaviour, as delineated by Brakus et al. (2009). This dimension bears a strong connection to Fishbein & Ajzen's (1975) theory of reasoned action, which posits that an individual's attitudes and beliefs dictate their behaviour. Consequent studies have discovered that positive brand experiences can amplify consumer loyalty and commitment (Chaudhuri & Holbrook, 2001; Oliver, 1999; Tran et al., 2023), as well as propel positive word-of-mouth (Larsen, 2018; Zeithaml et al., 1996). Moreover, Schmitt's (1999) insights on experiential marketing underscore the crucial role of actions and interaction in fashioning unique brand experiences.

In terms of the intellectual dimension, this involves cognition and thinking in brand experiences, according to Brakus et al. (2009). This dimension embraces aspects like mental stimulation and learning, reflected in how consumers process information and address problems (Pieters, 2010). Scholarly work on information processing proposes that advertising and brand communications can shape consumers' beliefs and product or service expectations (Keller, 1993; Petty & Cacioppo, 1986). Furthermore, neuromarketing research has shed light on the influence of brand experiences on cognitive processing and brain activity (Plassmann et al., 2012; Woodham et al., 2017).

Brakus et al. (2009) define the affective dimension as the emotions and feelings that consumers undergo during brand interactions. The theory of emotion in marketing implies that emotional experiences significantly shape the development of consumer attitudes and behaviours (Bagozzi et al., 1999; Volo, 2021). Studies rooted in consumer psychology have highlighted various emotions like joy, surprise, sadness, and anger, which brand experiences can trigger (Lazarus, 1991; Richins, 1997).

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