

2025

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Recommended Citation

Bayram, Ali Turan and Alshakhatreh, Ibrahim (2025) "Tourism and E-Tourism: A Systematic Literature Review and Future Research Agenda," *AUIQ Humanities and Social Sciences*: Vol. 1: Iss. 1, Article 5.

DOI: <https://doi.org/10.70176/3106-7557.1004>

Available at: <https://ahss.alayen.edu.iq/journal/vol1/iss1/5>

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ORIGINAL STUDY

Tourism and E-Tourism: A Systematic Literature Review and Future Research Agenda

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ABSTRACT

In recent times, tourism, especially e-tourism, has been catching the attention of researchers and scholars. Numerous studies have emerged aiming to explore internet technology's role in transforming the tourism industry. This investigation aims to offer a systematic and state-of-the-art review of previous research on tourism and e-tourism based on sentiment analysis, a technique used in previous studies. Sentiment analysis is chiefly concerned with the analysis of tourists' sentiments expressed in their reviews and experiences shared on digital platforms. To conduct our study, we relied on literature reviewed from three major digital databases, including Science Direct, IEEE Xplore, and Web of Science. We selected 41 articles divided into four major categories through the filtering and screening process. A detailed review of the studies in these four categories has been provided. We also performed a mapping analysis to make this review more robust and conclusive. In the end, we proposed some important future research agenda based on the TCCM (Theory, Context, Characteristics, and Methodology) framework.

Keywords: E-tourism, Tourism, Sentiment analysis, Mapping analysis, Systematic review

1. Introduction

The tourism industry constitutes an integral sector of a country's national economy and a major source of earnings. It can remarkably contribute to a country's sustainable development. Certain countries across the globe derive a major portion of their national income from tourism. For instance, the USA generates \$210 billion annually from tourism, while Spain draws \$ 68 billion per year from tourism. Similarly, some countries are exclusively dependent on income from tourism; for instance, in Maldives, 38.92% of the total GDP is obtained from tourism, and the British Virgin Islands makes 32.96% of its total GDP from tourism. In recent years, Tourism has developed into one of the most important components of many countries' sustainable development goals, and it seeks the utilization of sustainable business models that can contribute further to economic development.

To address the agenda of sustainable development, countries must be concerned with increasing tourists' satisfaction and enriching their tourism experience. The level of tourism in a country indicates its international reputation in terms of safety and facilities for tourists. Countries are finding new ways to promote tourism, and e-tourism has evolved new ways to flourish tourism. E-tourism refers to the digitisation of the tourism industry, which encompasses the entire plan and infrastructure of the tourist sector. With the development of the internet and Web 2.0 technologies, there are numerous opportunities for promoting tourism. Information and communication technology (ICT) has transformed the tourism industry and has been facilitating tourists to make an informed choice of tourist destinations. ICT has empowered tourists in terms of identification, customization, and purchase of tourism services and products and contributes to the global promotion of the tourism industry through

Received 27 August 2025; revised 4 October 2025; accepted 13 October 2025.
Available online 3 November 2025

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<https://doi.org/10.70176/3106-7557.1004>

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engagement in the development, management, and distribution of tourism facilities across the globe. Increasing reliance on ICT has prompted competition in the tourism industry to provide more facilities in order to become the foremost priority choice of tourists. The exchange of tourism-related information and instant access to such information has become the pivotal feature of tourism firms. ICT facilitates tourism firms in terms of the effectiveness and transparency of online information [1, 2]. Tourists are mainly dependent on ICT for information search and planning of their trips and are also eager to share their tour experiences online [3, 4]. Accordingly, tourism firms are striving to make efficient use of ICT to attract tourists.

With the expansion of tourism and e-tourism, researchers' interest in the field has grown manifold; over the last few years, many studies have been conducted to investigate various aspects of tourism and e-tourism and the role of internet technologies for the transformation of tourism industry. This paper provides a state-of-the-art systematic review of the studies conducted in the context of tourism and e-tourism. For this purpose, we relied on sentiment analysis techniques to comprehend our review. Sentiment analysis is described as emotional polarity, and it aims to find positive, negative, and neutral expressions in the text. Sentiment analysis is one of the sub-components of text mining and is based on understanding the emotion in whole or part of a text with computer-based techniques [5]. Knowledge of customers' opinions, attitudes, and feelings about products and services helps organizations understand the degree of satisfaction of their customers, which is very important in the decision-making process.

The utmost functional aspect of sentiment analysis is to examine tourists' sentiments. Filtering and machine learning are the most used techniques in the sentiment analysis of tourists. Filtering classifies words according to positive, negative, and neutral moods and places them in particular classes according to the sentiment analysis of each term. Sentiment analysis for tourism research allows tourists with various emotions to be analyzed within the scope of specific theories. Exploring the online comments that contain millions of bytes of data with the word filtering approach creates desirable systemic integrity for research [6]. Online reviews are used to determine the satisfaction, perception, and reliability of tourists and brand value. They have a distinctive role in the choice of hotel businesses; for example, before tourists prefer hotel businesses, they examine the reviews about the business from platforms such as TripAdvisor, Google comments, Facebook, or Instagram and choose businesses with more positive

comments and likes. Kim et al. [7] found a similar result and found that online reviews are the main factor in tourist preference while hunting destinations. Based on the analysis, 41 papers are classified into four major parts based on the aim and objective that meet the pre-specified inclusion and exclusion criteria.

2. Method and material

Three digital databases were selected for the purpose of conducting a targeted article search. These databases include (1) ScienceDirect, which provides access to journal articles in the fields of science, technology, and medicine (STM); (2) IEEE Xplore, a library containing technical literature related to engineering and technology; and (3) Web of Science (WoS), a service that indexes research spanning various disciplines such as sciences, social sciences, arts, and humanities. The motivation for their choices is to encompass technical literature in order to offer a more comprehensive perspective on researchers' endeavors and their pertinence to many fields of study.

The article-picking process involved several phases, starting with a search of literature sources. Subsequently, two further rounds of screening and filtering were conducted. During the preliminary stage, superfluous and redundant articles were excluded based on a thorough analysis of their titles and abstracts. In the succeeding iteration, the articles underwent additional refinement through a complete evaluation of their full-text content, building upon the previous screening process. The authors that conducted the screening and were evaluated by all authors applied the same eligibility criteria in both rounds.

2.1. Search

The most vital keyword in the scope of this paper is "Sentiment Analysis" and "Tourism" or "e-tourism". The search was conducted at the start of November 2022 in ScienceDirect, followed by WOS and IEEE Xplore through their databases accordingly. The keywords in terms of abbreviations are also taken into consideration while searching the databases. We further used the filtering features in each search engine to exclude book chapters and other types of reports apart from journals and conference articles. The exact query used in this research is ("Sentiment analysis" AND "Tourism" OR "E-tourism"). The finalized 41 articles are refined by ensuring that there are not duplicated articles. Among 41 articles, there are (21) ScienceDirect articles, (11) IEEE Xplore articles, and (9) WoS articles.

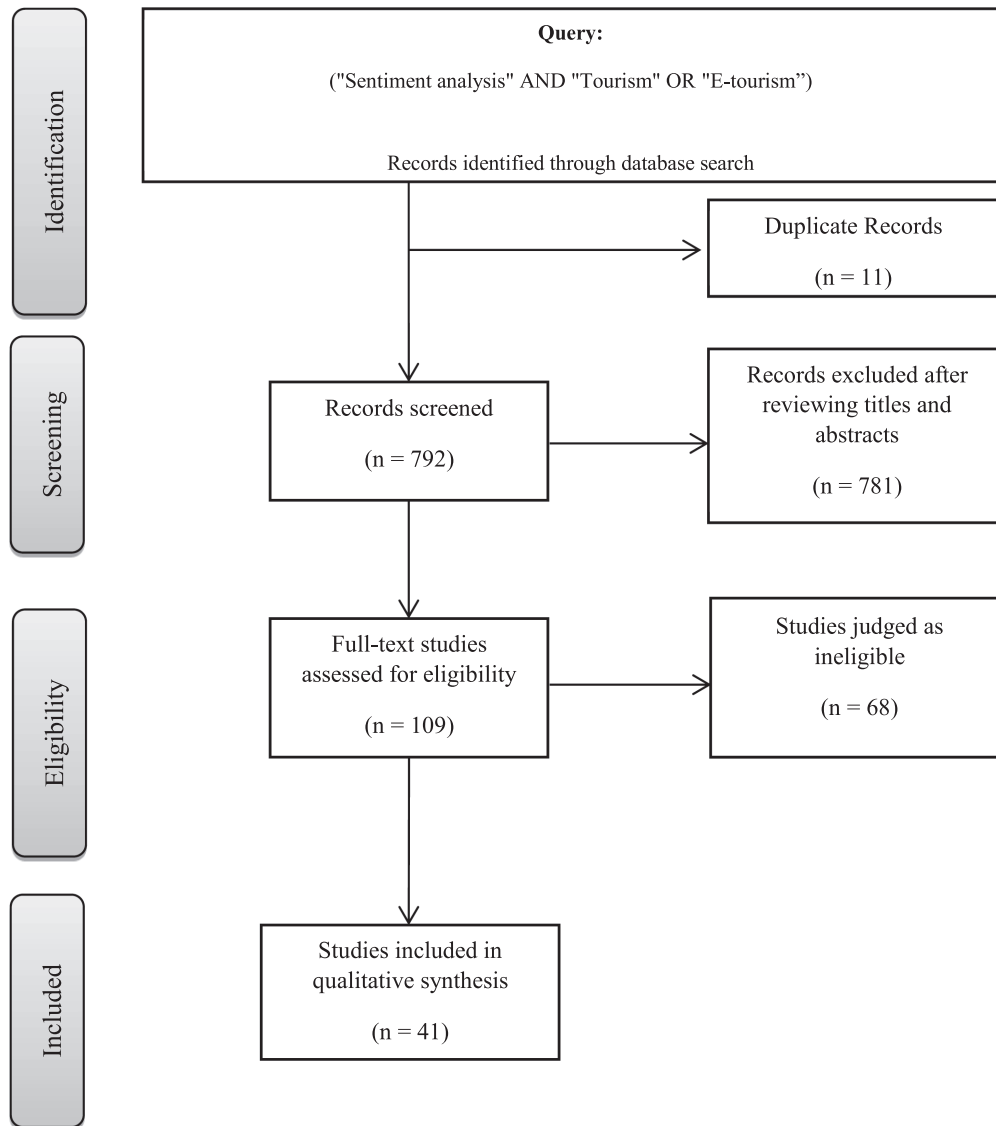


Fig. 1. The process of screening and including related studies.

2.2. Data Collection Process

The data collection process related to this topic starts with searching the ScienceDirect database, followed by IEEE Xplore and WoS databases. Once the search had been concluded, it was found that there were many existing studies similar to our initially defined search terms in general. All the related files were sent to EndNote for filtering purposes, and as a result, 19 closely related articles to this topic were selected and compiled into a single word file. In order to organize the collected information, a table has been created consisting of 3 main headers: title, country case, and source of data, as shown in Fig. 1.

2.3. Taxonomy

The tourism industry is a crucial element to all the countries in the world as every country wishes to benefit from the bounties of tourism. Tourism is one of the easiest ways to enhance revenue and raise employment in the country. The reputation of the country is also recognized through the national income gained from the tourists who visit particular countries. By doing this, the income collected from the tourism source can be invested to improve facilities, services, and attractions touring resorts. There are several questions that need attention, for instance: (1) How can the tourism industry be developed and

improved? and (2) What are the elements or aspects that need to be taken into consideration?

Tourists experience a very complex decision-making process when they need to balance between needs and affordability with regard to traveling to another country, choosing tourist destinations, suitable hotels, and restaurants. In general, tourism texts present a brief overview and information about a country, city, tourist spots, or hotels, which aims to attract the attention of the readers to encourage them to visit these places and facilitate their choices of destinations. Tourism texts are intended for the purpose of introducing tourist spots and destinations for the public to discover and enjoy. Tourism can be defined as an activity through which direct integration takes place between the diverse cultures in the world and the language. In line with this statement, it can be defined that the tourism industry acts as the mediator between the tourists, destinations, and their cultures. Besides, in order to build a cultural bridge between languages, translation comes in handy. It can be very useful when tourists from different nationalities are eager to obtain specific ideas and information from tourist texts such as brochures, banners, and publications. Therefore, it is essential to understand the tourist texts on different websites and in other languages.

All the articles were classified into four main categories, which consist of tourist places and historical cities (first category), hotels and restaurants (second category), countries (third category), and a combination of public responses to crisis communications thru the early phases of Covid-19, mixed restaurants, sightseeing, hotels, activities, nightlife, transportation, shopping, sporting and outdoors, and favourites (fourth category). There are enormous websites these days that help tourists in choosing appropriate travel destinations as well as determining the accommodations or hotels, for instance, TripAdvisor, Expedia, and Yelp. These platforms provide convenient spaces for users to share their hotel stays and travel experiences through user-friendly reviews. In this study, we employ sentiment analysis to examine tourists' reviews and introduce a novel metric for evaluating destinations' carrying capacity, primarily centered on TripAdvisor online reviews [8]. The results of our analysis demonstrate that destination managers can effectively employ the emotional index as a means to gauge the carrying capacity of their destination.

3. Results

Based on the analysis, 41 articles are categorized into four major categories based on the aim and objective that meet the pre-specified inclusion and

exclusion criteria. Each category was analyzed; the major category contains (n = 41) articles relating to:

1. The first category, tourist places and historic cities consists of 6 articles.
2. The second category is hotels and restaurants, which consists of 17 articles.
3. The third category, countries which consists of 8 articles.
4. The fourth category, a combination of topics related to crisis communications during Covid-19, sightseeing, activities, nightlife, transportation, shopping, sporting and outdoors, and favourites, consists of 10 articles.

3.1. Tourist places and historic cities

There are 6 articles related to the first category which discuss tourists' resorts and historic cities. During the COVID-19 pandemic, tourist places and cities were negatively impacted, which caused unprecedented havoc to the global tourism industry. In order to overcome this issue, several empirical studies were conducted to examine the impact of the Covid-19 outbreak on tourists' real-time on-site emotional experience using geo-tagged check-in user-generated content data in China's National 5A scenic spots from 7th November 2019 until 8th November 2020 [9]. This study mainly used questionnaires and interviews to measure tourists' emotional experience, which captured tourists' remembered experience only without the real-time on-site emotional experience, generating bias and inaccurate information gathering. In order to solve the bias, User-Generated Content (UGC) sentiment analysis is applied to measure tourists' emotional experience. The UGC sentiment analysis is applied to the data collected from Sina Weibo related to the emotional experience expressed on the check-in pages on social media. By doing this analysis, the results portray empirical evidence and practical implications towards destinations depending on the tourist experience management during and after the COVID-19 pandemic. From the evidence, it can be seen that tourists' emotional experience is significantly affecting the tourist destinations.

Prior studies carried out by earlier scholars examined a methodology for automatically grouping users based on the sentiment expressed in their reviews on digital tourism platforms [10]. The effectiveness of this algorithm was assessed using data obtained from the cultural and social information system called Cuscarias. It's important to note that categorizing disagreements related to specific aspects can be challenging, as it hinges on the sentiment polarity associated with the evaluation in question.

In a recent study [11], a sentiment-analysis technique was employed to assess the assessments of Chinese tourists on destinations in Australia. These evaluations were afterward compared to the evaluations generated by foreign tourists. The study employed lexicon-based sentiment analysis to extract the attitudes expressed by Chinese travelers in their online reviews of tourist locations and destinations. The data on internet reviews is sourced from prominent travel websites in China, such as qyer.com, mafengwo.com, and Ctrip.com. Upon concluding the analysis, it is evident that Chinese visitors' market characteristics and preferences continue to exhibit significant distinctions compared to international tourists. This observation underscores the crucial and ongoing need for continual monitoring and examination. Other researchers [12], conducted research with the objective of creating a novel metric for assessing the carrying capacity of locations. This metric is derived from sentiment analysis conducted on online reviews from the TripAdvisor platform. The present analysis is focused on the urban area of Berlin and encompasses the temporal span from 2013 to 2019. This research endeavors to construct an emotional index that reflects the level of emotional intensity experienced by tourists in a given destination throughout the designated period of investigation. The empirical evidence demonstrates that destination managers have the ability to utilize the emotional index as a means of quantifying the carrying capacity of a certain destination.

Researchers [13] suggested a mixed method approach including sentiment analysis and Latent Dirichlet Allocation (LDA) topic modeling. The methodology is specifically tailored to extract a large number of tweets about Lombok and Bali's regions, originating from Twitter users who are not local residents. These tweets were generated following a sequence of earthquakes in August 2018 in these two locations. The primary conclusions of the study indicate that, overall, individuals have exhibited a decreasing tendency towards negativity when expressing their opinions on Lombok and Bali. This trend has persisted despite fluctuations in the central trends of sentiment polarity.

Furthermore, a recent study conducted by [14] introduced a fresh and comprehensive methodology that incorporates various analytical methods, including sentiment analysis and topic modeling. The aforementioned methodology is employed to extract sentiments and subjects of interest from conversational data provided by travellers on the TripAdvisor platform, spanning the years 2002 to 2019. In addition, the authors additionally contemplate the examination of destination loyalty declarations through

the utilization of a term clustering methodology. Despite the presence of several restrictions stemming from the subjective nature of online reviews, the outcomes of this study make valuable contributions to the fields of academics and tourism in multiple dimensions.

3.2. *Hotels and restaurants*

The second group consists of 17 articles discussing hotels and restaurants from the tourist's point of view. By analysing sentiments on different websites, it can aid tourists in determining their travel destinations and choosing the best hotels and restaurants during their stay. Presently, several studies have been conducted specifically focusing on the reviews of hotels and restaurants.

Researchers [15] investigated the role of user-generated photos in online hotel reviews gathered by TripAdvisor. The researchers analyzed the mechanisms involved in generating images and investigated the impact of user-generated photos on the provision of online hotel evaluations. The data indicate that individuals are more inclined to share photographs of hotels that offer superior service quality, luxurious accommodations, and an overall favourable experience throughout their visit.

The task of identifying an appropriate hotel that aligns with the user's requirements and financial constraints is a formidable undertaking, including a multifaceted decision-making process. To facilitate the intricate process of decision-making, a recent study conducted by [16] introduced a new methodology for a recommendation system based on user queries. The present query system facilitates travellers in accessing reviews pertaining to hotels that align with their specific preferences and requirements. The integration of the proposed system with existing tourism systems can be achieved through multiple approaches. Rather than engaging in a casual search for hotels with favorable ratings on different internet platforms, travelers may consider using a more systematic strategy to choose accommodations within a certain location that possess desired attributes such as competent staff, quality services, ethical ideals, and positive evaluations.

Previous researchers [16] have put up a conceptual framework that examines the various aspects impacting sleep quality in hotels, taking into account both personal and hotel features. Through the analysis of hotel reviews on TripAdvisor, a model is presented that categorizes the elements influencing the quality of sleep experienced by hotel visitors. These factors are classified into two significant domains: personal characteristics and hotel characteristics. Each domain

has multiple distinct attributes. The findings confirm the effectiveness of the conceptual model that has been proposed.

On the other hand, there is another approach called object-based opinion mining. Researchers [17] implemented object-based opinion mining by applying filters on the object extraction process of the hotel and restaurant review data. The results obtained from this approach are quite satisfying; however, it consumes longer time in analysis as compared to other approaches, which is considered a drawback. For example, object-based opinion mining takes 3,051 seconds to extract the hotel review data and 1,559 seconds to extract the restaurant review data, whereas another approach takes less than 4 seconds to process the extraction of objects.

A tool embedding cloud-based technologies has been developed to analyze the sentiments of gastronomic establishments by previous researchers [18]. This tool helps carry out all the necessary steps related to the analysis, from downloading data to displaying results, including the intermediate stage of pre-processing, cleaning, data preparation, and dimensionality reduction. The tool is highly efficient in validating the gastronomic context of the Province of Granada, Spain. Researchers [19], proposed a tourist site ranking model of a city based on an Ordering Weighting Aggregation (OWA) operator. The aim of the study is to ensure that the tool acts as a recommender system based on the polarities gained from the users' reviews posted on social media. The accuracy and applicability of the tool is tested and proved using real datasets of the tourist sites in Paris.

There are hidden assumptions that were overlooked in evaluating the hotel reviews. This gap is explored by [19], which focuses on three underlying assumptions that are commonly found in online review research. These assumptions include (1) the assumption that all online users have equal visibility to all reviews, (2) the assumption that the helpfulness of reviews is influenced solely by the review rating and the hotel's star class, without any interaction between the two factors, and (3) the assumption that the characteristics of reviews and the status of reviewers remain constant throughout the study. The research conducted on the data gathered from TripAdvisor.com reveals limitations about the generalizability of the study. This is due to the restricted analysis done on hotels in two selected cities. Although this analysis fulfills the goal of examining two cities that are very different in the characteristics of their attractions, the results cannot be generalized to the entire hotel industry.

Researcher [20] proposed a platform for extracting and paraphrasing opinions expressed by users

on tourism-related online platforms. The proposed system extracts hotel reviews from the internet and classifies them using an opinion mining technique. The proposed technique has an acceptable accuracy, which is domain independent and does not need expensive resources to operate. Zhu et al. [21] introduced a novel approach to enhance sentiment word embedding through the utilization of a kernel optimization function. The objective of this approach is to combine semantic, statistical, and sentiment information while also preserving the similarity of sentiment words based on their sentiment orientation. The analysis was conducted using the data obtained from Qunar.com and Ctrip.com. The findings indicate that the sentiment vectors that are optimized effectively capture the properties related to sentiment information, as well as the distinction between the concretization and abstraction of sentiment words.

Marcolin, Becker et al. [22] also present and substantiate a framework aimed at optimizing the utilization of textual data within the hotel business. The researchers integrated three distinct text mining techniques, namely text categorization, sentiment analysis, and topic modeling, which collectively formed a unique and innovative approach. This methodology enables managers to assess guest comments and make comparisons across competitors in the hotel business using the SERVQUAL model, with the aim of enhancing service quality within the tourist sector. One advantage of this technique is in its potential to offer a precise characterization of the examined hotel industry. When it comes to rating of tourists' experience, there arises an issue with TripAdvisor bubble rating, which shows that users tend to evaluate overall experience positively even though they experience several negative experiences during their travel. Valdivia et al. [23] were the first group of researchers who pointed out this issue and proposed a polarity aggregation model to solve the problem. This study presented the model as a unified index of two polarities comprising User Polarity and Sentiment Analysis Methods (SAMs) Polarity. This model is guided by the geometric mean function of the User Polarity and SAMs Polarity on an Aspect-based Sentiment Analysis (ABSA) scenario.

[24] conducted a study distinguished from the presently available research. They use gaming features and apply them to non-game contexts to engage users well. The changes in user behaviour become a gap in this research area. They studied how gamification features can affect the changes in user behaviour effectively. The gap is filled by implementing a data-driven approach on a total of 67,685 online reviews collected from TripAdvisor from 2016 until 2017.

Four ANNs were competent in modeling two pairs of elements consisting of the title and review's word length and the title and review's sentiment score. On top of that, points and badges available on TripAdvisor were also considered as inputs when implementing the 12 gamification features. As a result, it is proved that the tool developed by embedding gamification features is able to motivate travellers to interact and contribute their reviews on the TripAdvisor site. [25] conducted an investigation on the factors that impact user experiences on Airbnb by evaluating a large dataset of online reviews. The analysis is conducted using the methodologies of text mining and sentiment analysis. The findings of this study indicate that Airbnb customers tend to assess their experiences by comparing them to their previous hotel stays and other alternative methods rather than forming a comprehensive picture of their current Airbnb experiences.

Most of the existing researchers focused their study on user's experience. However, [26] direct the research into organizational influences in the hotel industry. The authors propose a conceptual framework for analyzing the underlying mechanisms via which organizational agility impacts hotel performance, with a particular focus on the mediating function of social media, mobile, analytics, and cloud (SMAC) technologies. The system underwent testing by utilizing a dataset consisting of matched data from hotel practitioners and the corresponding customer reviews associated with each assessed hotel on the TripAdvisor platform. The results validate that the effective implementation of SMAC holds promise in fostering favourable word-of-mouth and enhancing customers' opinion of hotel quality. The results verify that the proper deployment of SMAC has an opportunity to develop favourable reviews and enhance the impression of customers toward hotel quality. The results verify that the proper deployment of SMAC has an opportunity to develop favourable reviews and enhance the impression of customers toward hotel quality. The tourism business experienced adverse effects as a result of the Covid-19 outbreak. To mitigate the consequences, the tourism sector has transitioned towards virtual tourism. [27] conducted a study in the virtual tourism business to investigate the public mood and drivers of virtual tourism. The researchers employed the Python programming language and the grounded theory approach to analyze the data. The findings indicate that the majority of tourists express positive feelings in the context of virtual tourism, whereas a smaller proportion of travellers exhibit negative or neutral attitude polarity.

[28] investigated the correlation between emotional inclination and electronic Word-of-mouth

(e-WOM) conveyed across four stages of tourist travel experiences, adopting a multiplatform approach. This aspect has received limited attention within the domain of tourism management research. Sentiment analysis was conducted utilizing reviews from two platforms. The findings suggest the presence of a discernible emotional polarity. Moreover, it is shown that pleasant feelings tend to occur more frequently in comparison to negative emotions when individuals engage in travel experiences. There exists a distinction in emotional polarities between male and female travellers. A tourism recommendation system was proposed by existing researchers to extract user preferences to provide personalized hotel recommendations [29]. The system uses datasets available on the TripAdvisor platform to come up with recommendations. The evaluation findings demonstrate that the suggested system outperforms the existing systems in terms of the f-measure criterion.

4. Benefits of sentiment analysis in tourism

Sentiment analysis, separating positive and negative thoughts, is the process of determining positive and negative opinions, feelings, and evaluations. It can also analyze multi-perspectives, question answering and summarize opinion-based information extraction, and data mining product reviews at the sentence and expression levels [30]. In addition, it is also seen as a dynamically growing field of natural language processing [31], denoting a significant problem area known as opinion mining—a field of study that analyzes people's views, evaluations, attitudes, and feelings towards entities such as products, services, organizations, individuals, problems, events, issues and qualities [32]. Social media tools represent excellent data source for sentiment analysis since they try to detect people's feelings and thoughts through a written text. Machine learning techniques and the rise of data sets have helped to eliminate the difficulties of sentiment analysis with internet-based developments [33]. However, sentiment analysis applications are getting more and more complex with every passing day (Fig. 2).

While simple two-class problems are analysed between the time span from past-today, more complex issues are carried out with external factors. For example, e-mail has long been divided into harmless, spam, or malicious mail. However, today, inferences can be questioned whether the difference between people watching a movie is due to the viewer, actor, director, scenario, or a different variable. People benefit from the feelings and thoughts of other people and see their experiences as a guide for themselves



Fig. 2. Benefits of sentiment analysis in the tourism industry.

while making decisions. It is possible to reach many people's feelings, reviews, and ideas on many issues with social network development. However, it is not possible to read and evaluate all of them. Sentiment analysis, which comes into play at this point, allows people to group their feelings, thoughts, and ideas as positive, negative, or neutral. Although sentiment analysis may seem simple, it is very complex and challenging. The fact that all the words in the text do not express emotions makes it necessary to separate the words first [34]. Learning about emotions is of great importance in terms of increasing service quality, en-

hancing customer's satisfaction, and ensuring loyalty in the tourism industry, The opportunities in social media tools also offer great convenience in terms of learning emotions, in particular, opinion-sharing-based applications allow consumers' comments to be examined by business or marketing experts which reveal hidden emotions in the feedbacks.

The tourism sector has diverse touristic typologies; sometimes, feedback can only be received instantly, whereas in other cases, it takes a while, depending on the tourist's typology. In the latter situation, the tourists can share their experiences on social media

tools or the websites of businesses after their vacation. The sentiment analysis, at this point, offers the management or destination an opportunity to perceive whether the tourists' feelings about the business or their experience are positive, negative, or neutral. Making good use of these opportunities will positively impact the business or destination image. To illustrate, Rane and Kumar [35], analyzed the messages sent by six major airline companies in the USA and determined that the majority of the messages were negative, and the words "customer service problem" and "late flight" were frequently used in messages classified as unfavorable. Based on this data, businesses can learn about their problems and take measures to satisfy consumers. Sentiment analysis studies are carried out in the field of tourism as well as in many other areas; they are generally used in customers' relationship management when customers' emotions, attitudes, and evaluations are analyzed with the content produced by the customers [36]. Many sentiment analysis studies, usually addressing a company in tourism, are conducted using reviews for hotels and restaurants.

According to Mostafa [37], Sentiment analysis performs the process of classifying an opinion as positive (positive), neutral (neutral), or negative (negative). For instance, in the sentence "I liked the food very much even though the service was awful" in the customer's comments, an opinion was expressed about the assets of "service" and "food." The sentence is subjected to gaze/feature-based sentiment analysis, defining assets (service and food) as first. In addition, a view or opinion is drawn about these assets, and a positive, negative or neutral value is defined for each asset [38]. This method of investigation is considered necessary for document-level sentiment analysis [39]. The first study on sentiment analysis studies in the literature is seen as document-level sentiment analysis by Turney [40]. The first study on gaze/feature-based sentiment analysis was carried out by Hu and Liu [41]. There are very few studies evaluating customer reviews in the hospitality industry. Some of these studies are summarized below.

Behremen et al. [42], investigated complaints in hotels that offer "Halal Concept" services on the halalbooking.com site. According to the results, the most frequently complained service types are facilities, staff, and wireless internet. Prameswari et al. [43] used text mining techniques, sentiment analysis, and text summarization to evaluate hotels in Labuan Bajo and Bali, Indonesia. As a result of the findings, they determined the emotional poles of customer's comments. For example, the emotional pole of halal food is positive in the comments about food and beverages in Bali hotels. Similarly, Berezina et al.

[44] collected the online comments evaluations related to the hotels in Florida and Sarasota using text analysis methods from the TripAdvisor site. Results revealed positive and negative findings about sports fields, membership, furniture, and rooms. Acar and Uğur [45] revealed the feelings of guests staying in chain hotels regarding their comments and opinions on TripAdvisor. They examined 655 comments, and the hotel got a very positive score from the guests. Also, the guests' comments were based on "trust" and "pleasure," where guests' trust in hotels was relatively high.

Perikos et al. [46] applied sentiment analysis to the data set from an online hotel reservation site using machine learning. NB, ME (maximum entropy), SVM, and Ensemble (Community) algorithms were used, where moderate success was stated to be 82.25%. They obtained the best result with the Ensemble algorithm, which successfully performed at 86.00%. Yin et al. [47] used sentiment analysis with the machine learning method to the data from TripAdvisor.com and BeerAdvocate.com sites using Hierarchical Architecture (HM) and SVM algorithms. The average model success values of the classifications were 61.05% and 84.59% for the HM and SVM algorithms, respectively. Xia and Wu [48] scanned social media data to explore tourists' distribution characteristics and sentiment exchange patterns. By testing the Spatio-temporal changes in tourists' emotions, they found a negative relationship between the number of tourists and tourists' sentiments. For example, they found that the number of tourists was highest in October and lowest in March, but tourists' sentiment was highest in March and October. Finally, Al-Smadi et al. [49] applied sentiment analysis to a ready-made data set containing online Arabic comments on hotel customers using machine learning. As a result of supervised classification tests with SVM, KNN (K-Nearest Neighborhood), Decision Tree, Bayesian networks, and NB algorithms, SVM was chosen as the classifier that produced the most successful results with a prediction performance of 93.40%.

Hashim, Omar and Samarraie [50] reviewed previous studies by using sentiment analysis—a computational method to extract people's opinions on social media in the tourism industry. The most popular dataset, TripAdvisor, was used for analysis, while the most widely used sentiment classification Machine Learning Lexicon-based approaches were adopted. In their study, Guerreiro and Rita [51] applied sentiment analysis on 1,112,708 comments made to 47263 different restaurants in 661 different cities. The accuracy values in the study using LR, CART, and RF algorithms were 66.86%, respectively. They were calculated as 66.05% and 66.83%. Raut and

Londhe [52] evaluated 1000 positive and 1000 negative hotel reviews from TripAdvisor.com. Training and test data were divided into half, and a re-labeled ready-made data set was used in the analysis. The performances of NB (Naïve Bayes), SVM (Support Vector Machines), CART (Classification and Regression Tree) algorithms, and SentiWordNet method were compared. The accuracy values were 88.00%, 83.50%, 78.40%, and 87.60% respectively. Luo [53] conducted a sentiment analysis study on three various data sets with different dimensions. In the study, in which SVM, NB, and LR algorithms were used in the analysis phase, the average success rate in the data sets was 76.00%, 26.00%, and 71.00%, respectively. The textual information on the web is gathered under two categories; these categories contain information that expresses facts or ideas. Facts refer to objective sentences that do not contain any emotion. On the other hand, ideas are related to people's natural and general subjective descriptions of events and entities [54].

Ma et al. [55] provided a step-by-step guide to be used as sample textbook material for hospitality. Nayel et al. [56] used machine learning-based sentiment analysis on 3000 comments randomly selected from 12548 Twitter posts in the Arabic language. The SVM, LR, NB, and CNB (Complementary Naive Bayes) algorithms were calculated as 85.55%, 65.89%, 78.92%, and 83.47%, respectively. Wang et al. [57] applied machine learning-based sentiment analysis to 6000 Chinese hotel reviews selected from 11,600 comments they took from the web with the help of the method called Doc2Vec. The accuracy in SVM, LR (Logistic Regression), and NB algorithms was 84.30%, respectively, and calculated as 81.00% and 74.40%. With sentiment analysis, Buddha et al. [58] analyzed 4.1 million comments from cafes, bars, restaurants, etc. Although many algorithmic classifications are used in the study, RF, SVM, and LR algorithms are the common points regarding this study. The results were calculated as 87.95%, 90.57%, and 91.16%, respectively.

Sinoplu and Ceyhan [59] examined 1985 Tweets about the selected destinations. After sentiment analysis, they ranked destinations with the highest percentage of positive tweets. Bayram [60] determined that online consumer evaluations and responses to them affect the decision of consumers to purchase or not to purchase in the tourism sector, as in other sectors. The findings revealed that the criticisms made are mostly irreversible by the hotel businesses, and the comments that were answered were primarily positive. Wang et al. [61] used customers' ratings for hotels on the online booking site to validate the

sentiment analysis results applied to hotel reviews. They stated that the LRR (Latest Rating Regression) model they used to produce the best result (89.60%). Monitoring and improving travellers' sentiments and the level of satisfaction expressed in reviews, surveys, and online content is critical for DMOs and tourism destinations. By analyzing recorded views of individual businesses (hotels, restaurants, attractions, etc.). Data Appeal Company specializes in Sentiment Analysis and Reputation Management for destinations and tourism organizations. Online reviews and opinions (user-generated content) are increasingly affecting travellers' purchase power and decision-making. People tend to rely on the opinions of others to set expectations and reduce risk when making travel decisions. If travellers turn to online reviews about a destination and its hotels, restaurants, and attractions, the destination itself cannot ignore them. A destination can take advantage of leveraging online content to gain actionable insights. The online sentiment reflects the true perception of the local's and tourists' experience, emphasizing their expectations and preferences. Therefore, monitoring and analyzing online feedback is essential to develop a successful regional marketing strategy for any tourism destination.

5. Mapping analysis

Sentiment analysis is an important tool in the tourism industry. It can identify and measure customers' sentiments about a particular destination, hotel, or travel experience. By tracking customers' sentiments over time, tourism companies can gain valuable insights into how their products and services are perceived by travellers. Sentiment analysis can help tourism companies better understand how customers feel about the resorts. It can also provide valuable feedback about customers' satisfaction, experience, and brand loyalty. This can be invaluable for improving customer service and the overall experience of the customer. Sentiment analysis can also help tourism companies identify potential issues that could be causing dissatisfaction, as well as pinpoint areas of improvement. By understanding customers' sentiments, companies can gain valuable insights into what customers are looking for in their travel experiences. This can enable them to tailor their services and products to meet customers' needs. Finally, sentiment analysis can provide invaluable information when it comes to marketing and advertising efforts. By understanding their sentiment, companies can better target their marketing efforts and create more effective campaigns. This can lead

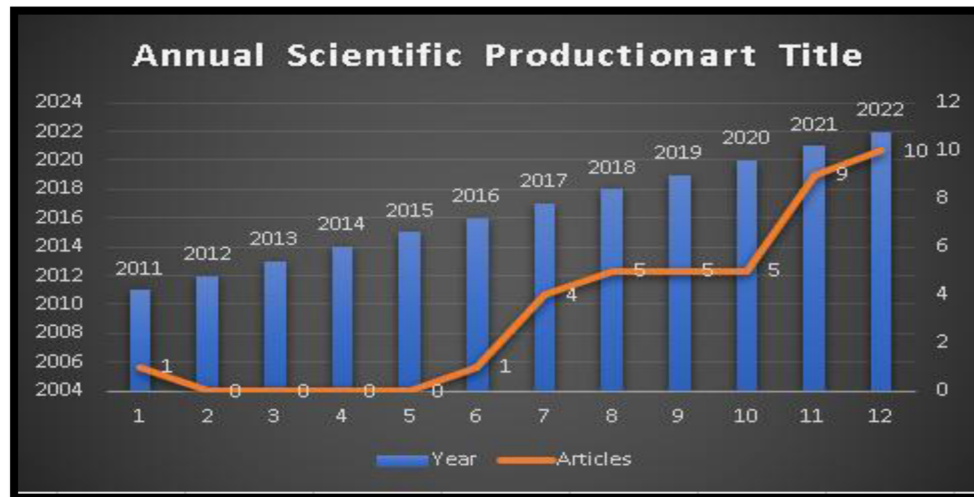


Fig. 3. Annual scientific production art.

to increased engagement and, ultimately more sales. Overall, sentiment analysis is a powerful tool for tourism companies to gain insight into customers' sentiments, identify potential issues, and tailor their services and products to meet their needs., By utilizing sentiment analysis, businesses can gain valuable insights into their customers' experiences and create a better overall environment for tourists.

An increased pattern of research was clearly noticed while reviewing the academic literature in progress on the topic of sentiment analysis and its application in the tourism industry. The amount of research applied in this area is considered a challenging task when researchers try to identify critical evidence from the previous studies. A number of researchers suggested adopting the PRISMA approach towards conducting a survey on newer problems and identifying research gaps. Systematic reviews expand the knowledge base, enhance the research plan, and synthesize the literature results. However, systematic reviews still suffer from the issue of reliability and objectivity since such approaches rely on the authors' perspective to reorganize the findings of the previous studies. To increase transparency in summarizing the results of the previous studies, several works have suggested methods for comprehensive science mapping analysis based on R-tool and VOSviewer—the bibliometric approach provides conclusive results, explores research gaps, and concludes findings from a literature review with high reliability and transparency. In addition, the above-mentioned tools do not require high skills and are considered open-source. Therefore, this study adopted the bibliometric method as shown in the following subsection.

5.1. Annual scientific production

Annual scientific production explains the production of theoretical and practical contributions of previous studies on sentiment analysis and its application on tourism. The pattern of annual research production is depicted in Fig. 3.

As shown in Fig. 1, 2022 is the most productive year, followed by 2021. After conducting an in-depth analysis of the collected articles, it was found that the reason behind this increment was the COVID-19 pandemic when governments stopped tourism activities aiming to stop/reduce the spread of the scourge. A number of researchers attempted to mitigate the consequences of this pandemic by developing sentiment analysis on tourism-related areas. This sector was heavily affected by the pandemic because most of the touring resorts were closed. The domino effect of the pandemic was obvious, which caused several other sectors to suffer. As a result, the transportation industry was badly affected. Therefore, before, during, and after the pandemic period was an interesting topic for researchers to study. Sentiment analysis is becoming an active area of research to understand human feelings with the availability of tools and data. It is also expected to have more research in this area in the near future.

5.2. Country scientific production

Many countries utilize natural language processing, particularly sentimental analysis tools, in the area of tourism. A country's scientific production illustrates the contributions of previous studies at the country

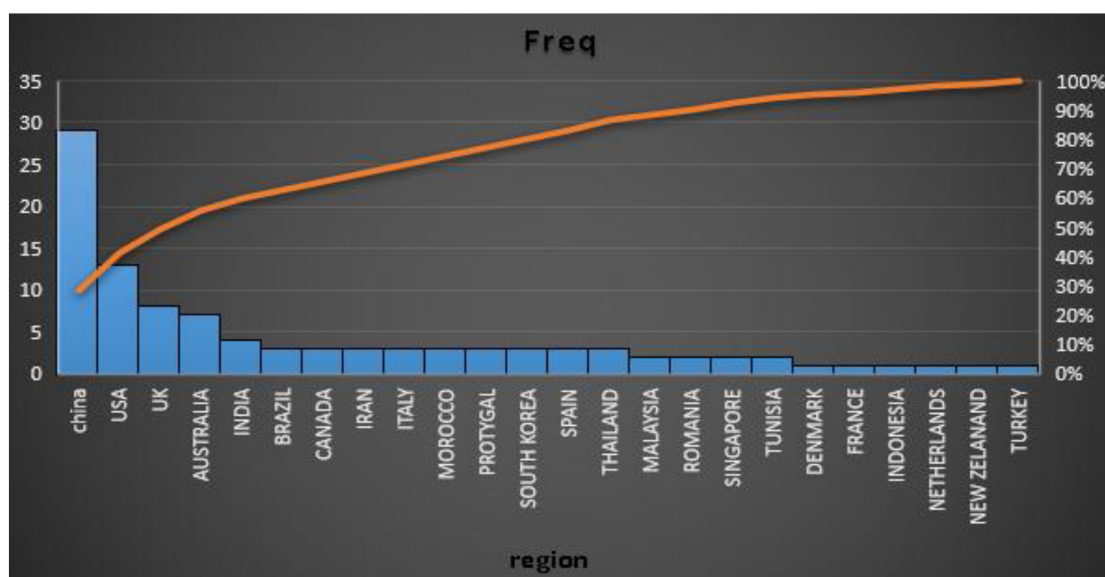


Fig. 4. Country scientific production.

level. Fig. 4 presents countries' scientific production to help the policymakers in a particular country to understand the tourism industry by analysing it through sentimental analysis.

China and the USA are at the top of the list with the highest paper production related to sentimental analysis and its application in tourism. The above-mentioned countries used data sciences tools to develop trustable tools, helping the industry understand human feelings towards tourism. They were followed by the UK, Australia, India, Brazil, Canada, Iran, Italy, Morocco, Portugal, South Korea, Spain, Thailand, Malaysia, Singapore, and Tunisia, while countries such as Denmark, France, Indonesia, Netherlands, Newzealand and Turkey were at the bottom of the ranking, despite the fact that these countries are among the highest visited during the year. Furthermore, the low annual production of countries may be due to a lack of expertise or other issues.

5.3. Word cloud

The word cloud identifies the most frequent and essential keywords in previous studies. Fig. 5 presents critical keywords in the findings of previous studies to summarize the broader picture of those findings and reorganize knowledge.

Fig. 5 displays keywords of different sizes. The larger size of the keywords is an indication that they appear more frequently in the literature. Conversely, the small size of keywords indicates that they ap-

pear less frequently in the literature. In the context of Sentiment analysis, tourism is one of the most vital topics in the previous studies. In addition, many studies in the literature have attempted to utilize sentimental analysis with the scope of topic modelling, sentimental classification, and polarities analysis in the tourism sector.

5.4. Co-occurrence

Co-occurrence networks pertain to the shared occurrence of terms as identified in prior research. Co-occurrence analysis is a methodological approach within the realm of semantic networks that offers valuable insights to professionals, policymakers, and scholars into the underlying conceptual framework of a specific area of expertise. Fig. 6 illustrates co-occurrence networks and detects frequently occurring keywords. The co-occurrence analysis demonstrates the interconnectedness of the topics through a network structure comprised of lines and nodes. The prevalence of large knots signifies the most often occurring themes. The academic literature extensively covers themes such as sentiment analysis in the context of tourism, encompassing social media, tourist destinations, and travellers' behavior. Through the utilization of data networks, policymakers and scholars can employ sentiment analysis to identify and analyze the frequent recurrence of keywords pertaining to tourism. This enables them to effectively restructure the existing information and findings, hence facilitating their efforts in the field.

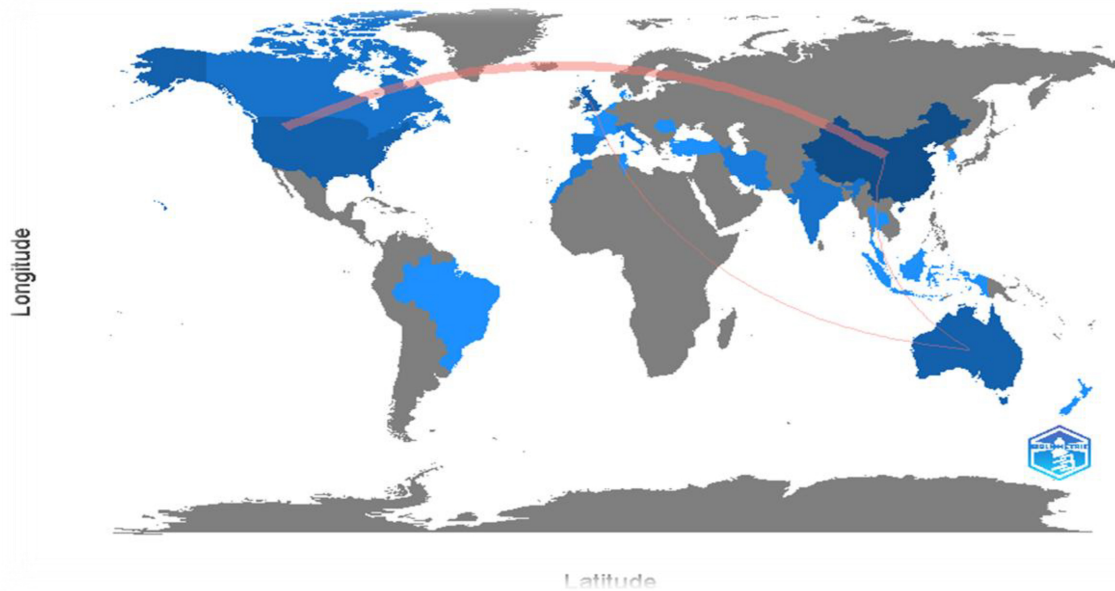


Fig. 7. Country collaboration map.

scientific production. Furthermore, the red line symbolizes the establishment of scientific collaboration among nations. Fig. 7 provides empirical evidence supporting scientific collaboration between Europe and America to advance and comprehend the tourism sector. This collaboration involves the analysis of social media data, specifically focusing on the periods during and after the occurrence of pandemics. Nevertheless, a notable deficiency in scientific collaboration exists among the continents of Asia, Europe, Africa, and the Americas. The absence of a specified rationale for this dearth of collaboration necessitates that policymakers and academics in the aforementioned regions explore novel approaches to foster and augment scientific cooperation. By leveraging the expertise and skills within this domain, they can emulate the collaborative efforts observed between the European and American continents, thereby reaping the associated benefits.

6. Future directions based on TCCM framework analysis

Based on the thorough review conducted, this section presents several useful dimensions of insight and enhances the impact of existing review-based suggestions by providing a broad direction for future research using the TCCM framework, which can be further discussed into theory, context, characteristics, and methodology [62]. This will help future researchers to seek gaps in each element in the TCCM framework, specifically in the tourism domain.

6.1. Theory

The review article published by existing researchers [63] focused on sentiment analysis in the tourism domain. The study in the tourism domain is considered dynamic and subjective due to the constant changes and different feedback provided by tourists from various backgrounds in terms of perspectives, reviews, and opinions towards tourist spots, historic cities, hotels and restaurants, communications, transportation, etc. While the research on the tourism domain is portrayed as subjective, the facts and information related to tourism can be supported by theory-driven approaches. This practice can provide detailed explanations and understandings of tourism phenomena, thus indirectly serving as a catalyst to push tourism research into a new era. As for now, existing works have neither considered the variables in other services and industries nor proposed any alternative comprehensive theoretical framework. However, researchers have used multiple theoretical approaches to support their studies producing a mesh of theories, such as grounded theory [64], stress theory [65], perceived risk theory [66], traveler's career theory [67], negativity bias theory [68], social-mediated crisis communication theory [69], arousal theory [70], push-pull theory [71], three-factor theory [72], goal hierarchy theory [73], real options theory [74], broaden-and-build theory [75], time geography theory [76], equity theory [77], and social comparison theory [78]. From the readings, it is obvious that these theories are biased towards several characteristics such as nationality, crisis response, tourists'

sentiments, organizational agility, social media, and others. Because of the diverse nature of these theories and the absence of a comprehensive theoretical framework, it has resulted in a vital gap and created hurdles in determining the progress in understanding the construct in the tourism research field. Thus, the current research provides the following recommendations to enhance the existing theory and overcome the gaps:

1. **Combination of data-driven and theory-driven approaches:** The study recommends future researchers to consider a combination of data-driven and theory-driven approaches when working in the tourism field. They will be useful for strengthening the outcome of the subjective tourism field. This is because the patterns of large datasets obtained from a data-driven approach can be combined with the theory-driven approach to develop and refine constructs and relationships among them. It will also help to identify the most distinguished theories used in this construct, which directly provides a clearer view of the framework for future studies.
2. **Theories expanded to other services:** The existing theories found in this study can be expanded to other services related to tourism, such as the shopping experience, use of websites for online purchases, watching sports or cinema, and different types of restaurants and shops to understand the tourists' perceptions and experiences.
3. **Usage of other quantitative research methods:** The proposed theoretical framework from existing works can be supported with the help of other quantitative research methods such as Social Media Analytics Capability (SMAC). This can be done by proposing a new theory to discuss the role of organizational agility in enhancing hotel performance with the support of SMAC.

6.2. Context

The contexts play a vital role in enhancing the tourism domain as there are diverse elements that need to be taken into consideration. Research in the field of tourism has resulted in positive and negative impacts depending on different contexts. Throughout the research, it can be seen that most of the publications pointed out the Chinese tourists' perceptions toward other countries they visit [79–81]. This could lead to biases and stymie on-point objective feedback in the tourism domain.

Majority of the existing researchers focused their studies on regional context [82–84] and language

context [85–91]. The existing works that focused on regional context highlighted tourists from China in their studies. Instead, diverse samples from various countries and regions are needed to compare the groups of virtual tourism and explore the formation mechanism under the influence of myriad cultural backgrounds and tourism development levels. Besides, as for the language context, the existing works only analyze the English language, thus neglecting other native languages. The opinions and perspectives of diverse tourists' backgrounds are helpful in enhancing the tourism industry despite differences in languages. A good deal of vital improvements could be missed due to the negligence of other languages.

Several contexts within the tourism field are under-researched, and vital assessments are missing from the literature. For instance, visual context, which is one of the crucial elements in tourism reviews, has been overlooked. Researchers have studied the importance of photo-based reviews instead of text-based reviews only; An et al. [92] come out with a conclusion that visual contexts should be taken into consideration as they portray more about the environments and surroundings nowadays. This will be helpful for tourists with various backgrounds to evaluate the tourist spots based on the photos, as they may have different preferences. Although other researchers extended their studies to different contexts, more research and publications are expected to be accomplished to gain a clearer picture. Thus, this study provides these recommendations:

1. **Consideration of diverse contexts:** Apart from regional context, language context, and visual context, more extensive and comprehensive studies can be done in cultural, experiential (shopping experience, use of website for online purchase, and watching sports or cinema), social, economic, and religious context. These contexts enable us to push forward the tourism industry, which involves tourists from different backgrounds, opinions, and interests. Among these contexts, the social context could be a great future research opportunity as new generations tend to seek travel information through social media platforms.
2. **Improving service quality:** Most countries entice tourists by opening new attractions, which could be a great ploy, but they overlook the service quality of existing attractions. The existing resorts need to be improved based on the analysis of different contexts in order to gain more tourists.
3. **Extraction of data from photos:** Researchers need to extend the current research towards

photo-based sampling to extract more accurate information from user-generated photos.

4. Evaluation of destinations: Future researchers should collect data from more travel websites, including public and private destinations with large sample sizes. They should also consider famous and lesser-known destinations in their studies to evaluate the difference in travellers' sentiments. Future researchers need to find a solution to encourage tourists to write reviews after visiting any destination, as it really helps to close the gaps found in attraction spots.

6.3. Characteristics

Tourism-based information has different aspects of characteristics. Throughout the study, there are many characteristics proposed in existing works that influence the tourism industry. In this review, the characteristics are categorized into several groups, such as tourists, public emotions, accommodations, and electronic word-of-mouth (eWOM), to ease the path of future researchers to investigate. The first characteristic relates to the nature of tourists, which is a very subjective topic. If the information obtained from this characteristic is well implemented, the demand of tourists can be fulfilled. This characteristic aids in understanding the different perceptions of tourists from diverse backgrounds and interests. The existing researchers studied the demographic and biopsychosocial nuances of the tourists [93], while some researchers took other characteristics, such as the type of visitors, for instance, well-behaved visitors or badly-behaved visitors, into consideration [94]. This is because the tourists might leave reviews that are either excellent, good, or bad based on their mental state at that particular moment. This will actually have a huge impact on the traveling decisions of potential or future visitors.

The second characteristic is public emotions. The public emotion discussed in this study is related to the political issues between different countries. As we know, traveling involves moving from one place to another despite long distances areas, cities, states, countries, and continents. Researchers found that public emotions shifted from political issues into tourism boycotts [95], which shows the negative impact of cyber nationalism on the Internet and social media. For instance, the crisis communication in Weibo issues shifted into a tourism boycott where tourists from mainland China angrily expressed that they would avoid visiting Hong Kong. By giving negative expression, the overall tourism economy was affected. A similar situation was faced by Thailand during the Covid-19 pandemic. Thus, researchers sug-

gested that the political issues should be avoided; instead, the focus should be centered on promoting the destinations, nature, food, and nightlife attractions to increase the quality of the tourism industry [96].

The third feature relates to accommodation. When planning for a travel, the first thing that comes into travellers' minds is the accommodation. The reviews related to hotels and Airbnb have the greatest impact on the traveling decisions to certain resorts. The majority of the existing works discussed the characteristics of hotels, such as location, facilities, and sleeping environment [97–99]. All these characteristics are considered as main preferences by tourists when deciding on hotels as they want ease of access to nearby facilities and a night of quality sleep. In another study, researchers also consider traveller's commitments as one of the factors in accommodation characteristics. By taking this factor into consideration, the travellers committed to sharing positive reviews, online reputation management, and a platform that generates comments or shares on posts, online ratings, online booking-call-to-action, and influential blogger posts [100]. Once travellers have the best experience with their staying, they provide positive reviews, which would boost the hotel's reputation. Indirectly, those hotels become the most preferred accommodation for future travellers as well. Apart from that, researchers also analyzed several factors such as multiculturalism, vibrancy, ease of transport, and safe environment [101]. These factors aid in the contribution of positive comments regarding the hotel as they come from the personal opinions and experiences of the tourists.

The fourth characteristic is electronic word-of-mouth (eWOM). There are very limited studies carried out on this factor [101, 102]. The eWOM could be used to integrate reviews from travel website reviews, hotel reviews, and social platform reviews. As these main characteristics are highlighted in existing works, this study provides recommendations for future research opportunities as follows:

1. Consideration of other tourist characteristics: Apart from the demographics' details and personal opinion, other characteristics such as gender, age, traveller type, and review types based on personal experience should be studied. It will help future researchers understand how different genders, ages, traveller types, and review experiences have a higher influence on the quality of tourism.
2. Avoidance of crisis communication: As obvious from the findings, it can be seen that the crisis of communication led to a tourism boycott.

Further research can be conducted on finding the effectiveness of promoting tourism in a time of similar political protests and boycott crises considering complex bilateral relations such as between mainland China and Taiwan or involving China and Japan at the international level.

3. Consideration of subsidiary characteristics of accommodation: Apart from hotel location, facilities, and sleeping environment, future researchers should consider hotel star ratings and reviews, nearby restaurant density, and the number of floors in a hotel in their studies. By doing this, additional valuable information and reviews can be collected to improve the quality of accommodations to attract new potential tourists.
4. Research on eWOM: Further studies should be carried out on eWOM on social platforms, such as Facebook, Instagram, and Twitter, as widely used by influencers. By doing this, it can influence the selection of traveling elements, thus becoming a catalyst to enhance the quality of the tourism industry.

6.4. Methodology

The existing studies implemented several methods to study the findings in the tourism domain. Researchers used UGC sentiment analysis to evaluate the emotional experience shown by tourists depending on geo-tagged checks in UGC data in China [103]. Initially, the sentiment analysis aspect-based review categorization was checked manually, which was prone to human errors [104].

In another study, descriptive analysis and regression analysis were done on hotel reviews from TripAdvisor, which focused on text mining [105]. Researchers also implemented a hybrid text-mining methodology to obtain the reviews [106]. Most machine learning applications in the analysis of online reviews are written in English, restricting the reviews from native languages [107]. As the online analyzed reviews are based on text only, they can be misinterpreted if the tourists use different languages apart from English. The lexicon-based method for sentiment analysis is implemented to identify the performance value at the destination level [108] against the wide outcome. Although existing works have proposed different methodologies to analyse tourism-related information, several areas of improvement could be investigated by researchers in the future:

1. Future researchers can consider real-time on-site emotional experience to be implemented in the UGC sentiment analysis method as it is more realistic and unbiased.
2. The analysis of reviews in different languages is needed in the future when using machine learning applications or deep learning algorithms.
3. User photo-based and object-based opinion mining analysis are needed to extract information with finer granulating, which improves object extraction performance.
4. In order to overcome class imbalance and reduce human errors, future researchers can implement Random Over-Sampling Bootstrap Aggregating-based techniques and focus on the availability of more qualified annotators.
5. The lexicon-based methodology can be further extended to be applied to different tourism contexts so that future researchers get a wide range of findings in the tourism domain.

7. Conclusion

The development of Internet technology has completely transformed the landscape of the tourism industry from traditional to e-tourism. Tourism firms and tourists are using information and communication technology extensively for the growth and development of the tourism industry. Recent years have witnessed remarkable growth in e-tourism, and it has also invited researchers to investigate the future prospects of the tourism industry. A bulk of research studies are available which show the growing interest of researchers in the field. In this paper, we reviewed the previous literature on tourism and e-tourism to provide a systematic and state-of-the-art review of the literature. We found that many of the studies in the field have used sentiment analysis to evaluate the perceptions, emotions, and experiences of tourists. Sentiment analysis is a modern technique that relies on the 'text' data available in the form of tourists' reviews and experience sharing. Sentiment analysis is aimed at understanding the tourists' emotions and views about the touring destinations. To sum up, we relied on three major databases, which include Science Direct, IEEE Xplore, and Web of Science. Database search provided us with research articles covering different aspects of tourism research. Through the filtering and screening process, we identified 41 articles and divided them into four major categories. The first category included 6 articles relevant to the tourist places and historical cities. In the second category, 17 articles were related to the research on hotels and restaurants. The third category consisted of 8 articles about touring countries, and the fourth category included 19 articles on tourism regarding sightseeing, communication issues in tourism during COVID-19, transportation, and other tourism facilities. In addition, we also used mapping analysis,

annual scientific articles production, country-wise production of articles, word cloud, co-occurrence, and country collaboration map to make our review more reliable and robust. One major finding from the literature revealed that the tourism industry was negatively affected during the COVID-19 pandemic, and this led to virtual tourism or e-tourism. Results of various studies showed that positive sentiments of tourists prevail over e-tourism. Research on the hotel industry in the perspective of tourism revealed that tourists are hesitant to share and post their negative experiences on tourism-related websites. It has been noticed that many of the studies have used sentiment analysis and its application in the tourism industry. We also noticed an increase in the number of scientific articles produced in 2022 as compared to the previous years. This was the result of many studies conducted as a consequence of COVID-19 for the tourism industry. Though we tried to conduct an extensive and exhaustive review, there are certain limitations. For example, the scope of our article search was confined to three databases. Hence, we suggest including more databases for future research. Similarly, we did not consider the conference proceedings in our review. Future research may also consider these proceedings. Last but not least, a review of interdisciplinary studies can broaden the scope and produce interesting results.

Conflict of interest

The authors have no any conflicts to declare.

Author contribution

This section specifies the roles and contributions of each author in this manuscript equilly.

Data availability

Authors mention whether the data supporting their findings is available publicly, under specific conditions or on request.

Funded

No financial support received for the manuscript.

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