Exploring the role of online visual information in pre- and post- tourism experiences

By Sijun Liu

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Approved by

Imran Rahman, Chair, Associate Professor, Nutrition, Dietetics & Hospitality Management
Yee Ming Lee, Associate Professor, Nutrition, Dietetics & Hospitality Management
Ashish Gupta, Professor of Business Analytics, Department of Systems and Technology
Pankush Kalgotra, Assistant Professor, Department of Systems and Technology

Abstract

Visual information significantly influences tourists' pre and post tourism experiences; it creates a vivid stimulation of the experiences and can provoke the tourists' imagination to better convey the favorable information. Considering the role visual information plays, it has received much attention in business and academics, both from the perception of tourists and organizations. It is an important data channel to understand tourism experiences, travel patterns, and individual tourist's preferences. The development of information technology enables researchers to comprehend massive-scale structured and unstructured online data. It provides an easy way to explore how the tourists visualize the destinations and engage with the tourism activities.

The objective of this dissertation is revolved around visual information and its implication in the tourism field, along with other online displayed information, explores how they make an impact on post-tourism evaluation and pre-tourism decisions. In order to achieve this objective, this dissertation takes the form of three independent studies hoping to uncover the pictorial content relevance in the tourism field from three aspects:

1. A comprehensive systematic review of existing literature on visual information analysis in the hospitality and tourism field.

2. An experimental study on understanding pre-tourism experience decisions, via Search Engine Result Page (SERP) displays.

3. 2. A mixed-method approach aim to investigate post-experience evaluation on P2P gastronomy tourism, by factoring in web-based attributes, including web photos.

The following section breaks down and designates the highlights in each study.

Study 1 is a systematic literature review paper taken a text analytic approach that aims to review, analyze, and synthesize visual content analysis in tourism studies adapting big data analytic methods underlying machine learning. The literature search was conducted through two channels by keywords: Web of Science (WOS) and Scimago Journal & Country Rank (SJR) listed 124 tourism, leisure, and hospitality journals. In total, 67 papers were identified and considered after criteria filtering. To enhance the understanding of selected papers, first, a general description is provided with a distribution of research articles by journal fields and publication time. Second, a citation network was conducted to identify the connections between papers. Third, through text clustering, seven latent topics were discussed in detail in the results. The gap addressed and identified in study 1, study 2, and study 3 built on the aforementioned gaps and aims to amplify the significant role visual information plays in tourism behavior.

Study 2 aims to investigate information cues displayed through Airbnb experience Search Engine Result Page (SERP) and how it influences potential tourists' decision-making. In order to expand and explain tourists' information processing and identify the mechanism of displayed information cues on Airbnb at discrete levels, an experimental design was adopted. As such, to be able to assess the effects in a valid way, this study simulates Airbnb SERP and segmented information cues based on web collected data using the principle of math quartile for price, ratings, reviews, and time spent, and thematic categories for promotional photos, and promotional cues, including scarcity message, conformity message, and credibility cues, to test tourists' selection. All the thematic categories were decided from the text mining results. In addition, based on the selection of the results, tourists share similar selection characteristics to form a category, the market segmentations are formed based on the shared characteristics in selection. The incorporation of host credibility has never been explored in the context of P2P marketplace through an experimental design, the result from conjoint analysis shows the most important attribute is the host credibility, followed by images and price during consumers decision making. Theoretically, it employed signaling theory and heuristic systematic model in explaining how tourists' processing online information. It successfully bridges the gap by introducing promotional photos and host credibility information cues in an experimental study. Methodologically, the text mining approach was taken in information cues segmentation, which serves as a solid foundation for conjoint analysis survey design. The survey-based conjoint analysis further identified important information cues to each level and provided insights into each market segment. The findings provide substantial practical implications for marketers, web information displays, and tourists' online information filtering, processing, and selection.

Study 3 selected gastronomy tourism, as a unique and growing tourism segmentation, aims to explore post-experience evaluation through Airbnb platform. This study adopted Satisfaction Disconfirmation, and the main contribution of this study is that it has taken a mixed-method approach in understanding gastronomy experiences post evaluation of the P2P platform (i.e., Airbnb). This research focuses on three areas of findings to explore post-evaluation and factors that might be influential to post-evaluation. First, this study examined 196,265 online reviews and used topic modeling to identify the major themes. The results have shown that LDA effectively identified six topics across all the reviews, which are (1) food city tour, (2) social interactions, (3) host, (4) local food culture, (5) beverage appreciation, (6) hands-on learning, ranked by topic importance. In addition to topic modeling, the study further performed sentiment analysis, aim to generate different sentiments reviews count for gastronomy experiences. Second, through Google cloud vision API, 1,331 photos were analyzed, and gained image insights through three aspects: colorfulness, face detection, object detection. Colorfulness was further integrated into OLS regression. Third, OLS regression explored the factors that have significant impacts on gastronomy experiences ratings, with a consideration of review sentiments, image colorfulness, host credibility indicator (i.e., length of experience), and neutralized review count (review count/length of experiences). Theoretically, it employed expectation disconfirmation theory, and this is one of the first studies exploring tourism experiences provided through P2P platforms and evaluating the impact of both textual data and image data on gastronomy experiences. It successfully combined big data analytics (e.g., topic modeling, sentiment analysis, image analysis) and traditional methods (i.e., OLS regression). Practically, for the hosts and service providers, the study findings provide insights into aspects that gastronomy tourists' care more about, and factors that influence overall satisfactions of post evaluation.

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I would like to grateful acknowledge the people who have been part of my academic journey, without their help, the completion of this dissertation would not have been possible.

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I am extremely thankful for the experience graduate school has left on my career and in my personal life. The experience taught me to embrace the ups and downs of life. However, remaining motivated during the course of a Ph.D. is challenging. During these four years, I give my hearty thanks to my friends and research mates for their encouragement, friendship, and valuable quality time spent on research. I am extremely grateful to my parents, who are always there to support and encourage me. Their patience, love, and care during my life journey made me who I am today. Lastly, I'm beyond grateful to my best friend and life partner, Nan Li, for always reminding me to grow and motivating me to do better every day.

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Chapter 1 Visual information analysis in hospitality and tourism applying machine learning: a systematic literature review from a text mining approach

1.Introduction

Recent advances in the machine learning algorithm offer researchers across disciplines a novel approach to processing unstructured data, such as image data. In the field of tourism and hospitality, visual information in the form of photos can indicate how tourists associate and interpret the destination (Pan et al., 2014; Zhao et al., 2018). Given the importance of visual information analysis in the tourism field, it is necessary to comprehensively review the research published in hospitality and tourism literature. A review and analysis of the current state of research, will provide academia with an overview of the role visual information has played in tourism literature and how it bridges the disciplines of computer science and tourism, as visual information analysis is one of the dominant areas of computer science research. Subsequently, tourism scholars can form a better research agenda for the future.

From the past few years, social media platform attention has shifted from text-centric to visually-oriented content, where visual information is becoming the new paradigm in tourism communication for pre and post trip planning (David Negre et al., 2017; Li & Xie, 2020). With the rise of social media and Web 2.0, perceptions of tourism experiences are highly influenced by user-generated content (UGC) i.e., photos, videos, and comments (Arefieva et al., 2021; Payntar et al., 2021). Hence, destination and tourism experiences are not limited to official destination marketing organizations (DMOs) (Leung et al., 2013). Tourism researchers had raised concerns about the lack of dissemination, utilization, and recognition of the visual content in tourism studies (Matteucci, 2013; Rakić & Chambers, 2010). Until the recent years, the literature on tourism user-generated visual content has grown significantly. The majority of tourism studies utilizing images and applying a qualitative approach with a limited sample size (Matteucci, 2013; Sofield & Marafa, 2019; Stone & Nyaupane, 2019), limiting the ability to generalize the findings. However, research using advanced machine learning models can successfully address this dilemma and has recently gained momentum. This has become possible due to advancements in web scraping tools that enable researchers to analyze massive-scale image data from the world wide web (Sheng et al., 2020). Because image data is multi-dimensional, the most popular choices for machine learning modeling are deep learning models that can analyze and process the image data. Since the tourism and hospitality discipline is witnessing the rise of deep learning modeling in understanding customer choices and perceptions, it is important to understand the current state of research to propose an agenda for future research.

Photos and visual data are making a revolution in tourism and hospitality research, as well as the growing interactions. Yet, no study reviews the current state of photos and other visual data usage in tourism and hospitality research over time. Thus, this paper provides an overview of visual information analysis on deep learning in the tourism context, aim to review, analyze, and synthesize visual content analysis in tourism and hospitality research. The relevant papers were collected from both journals and conference proceedings to perform a systematic literature review. First, general descriptive findings are provided: (1) distribution of research articles by journal fields and publication time; and (2) distribution of articles throughout time. Following the descriptive, an overview of the collected papers is described through (3) citation network and (4) latent topics that emerged from the systematic review using text analysis. Finally, this study provides future research directions for visual information analysis in tourism. The most important topics and studies are highlighted, and emerging topic may be presented for future research.

2. Background

2.1. Machine learning and visual information

Images are believed to be valuable data in both business and academia. They help make a first impression and effectively form perceptions of a destination, an environment, or a product (Singh & Formica, 2007). Due to the significance of pictorial elements in communication, researchers have proposed various approaches to analyze visual content. The most popular technique currently is deep learning. Synthesizing existing literature on visual information analysis that applies deep learning techniques in the tourism and hospitality field will provide understanding of the current state-of-the-art approaches across hospitality, tourism, and culinary areas, which in turn will provide a foundation for future research.

2.1.1 Machine learning in understanding image

Deep learning (DL) is a subset of machine learning. When neural networks started outperforming human performance, DL became one of the most important breakthroughs in computer vision. It has the ability to perform classification tasks and produce descriptive elements in photos (Ghosh et al., 2019). DL techniques have demonstrated improved predictive performance in many domains, including image classification (Affonso et al., 2017; Krizhevsky et al., 2012). They incorporate automatically learned features instead of requiring feature engineering as a separate step. Therefore, the hierarchical feature representations are conveniently extracted without too much effort in designing features (Gupta et al., 2018; Zhang et al., 2016).

Deep learning techniques include different models such as neural networks, hierarchical probabilistic models, and unsupervised or supervised feature-learning algorithms (Zhang et al., 2016). Several deep learning algorithms have been recently introduced to scientific communities in domains, such as Convolutional Neural Networks (CNN), Recurrent Neural networks (RNN), and Denoising Autoencoder (DAE) (Mosavi et al., 2019). CNN is a typical example of a deep learning model. Studies have suggested CNN is superior to traditional machine learning algorithms, such as K-Nearest Neighbors (KNN), for image classification (Affonso et al., 2017; Bengio et al., 2007). Since 2012, due to the increasing amount of labeled data as well as breakthroughs in training the model, gradient-based training has achieved decreased training time and higher accuracy rates.

2.2. Deep learning computer vision algorithms development

In 2012, ImageNet classification with CNN made significant progress. AlexNet achieved 50% reduction in error and provide a baseline for computer vision tasks. The study was the first to successfully use deep learning for large-scale image classification and train a model using parallel computations on two GPUs to achieve a reduction in speed; it set the bar for and provided a direction for future studies (Krizhevsky et al., 2012). The same year, researchers at Google's X lab built a neural network of 16,000 computer processors with one billion connections, and the network showed high sensitivity to concepts such as cat and human bodies. It obtained 15.8% accuracy (Markoff, 2012).

In 2015, both GooGleNet architecture and ResNet made a further advancement in reducing the computational power, achieving better performances in contributing to classification networks. GooGleNet was the first to address computational resources and multi-scale processing; this solved problems with deeper networks requiring more memory consumption and computations. It is also one of the first models that introduced the idea of non-sequential CNN layers. It revealed that in addition to network depth, expanding network width can achieve better performance (Szegedy et al., 2015). ResNet, on the other hand, improved in accuracy and mainly contributed to residual learning. It demonstrated that making the network deep might not be the solution for model improvement in terms of accuracy, in addition, the study proposed the idea of skip connection as a shortcut. In this way, deep residual networks can greatly improve accuracy through increased depth of network applied residual learning. The idea is When layers fit a residual mapping, the deep layers access features from previous layers. ResNet evaluated the residual network with 152 layers and achieved a 3.57% error rate in testing (He et al., 2016).

In 2018, DenseNet (Densely connected CNN) allowed each layer to use all the feature-maps as input and used its own featured-maps as inputs into all subsequent layers. It advanced the model, exceeded ResNet through concatenation, and reduced the number of parameters to a great extent. In addition, it minimized the vanishing-gradient problem (Huang et al., 2018). In the same year, there was a major breakthrough on object detection and image segmentation, with the development of more frameworks such as YOLO v3, R-CNN, Fast-R-CNN, Faster-R-CNN (Huang et al., 2017). From 2015 to 2018, Microsoft launched cognitive services, including computer vision. Google TensorFlow published an open-sourced framework for machine learning where its cloud vision image recognition API became available. Similarly, Tencent AI Lab introduced the open-source Tencent Multi-label Images (Wu et al., 2019).

All the aforementioned information on advancement in computer vision under deep learning provides means to applications in different fields. Followed by the significant time points of algorithm advancement, image analysis research and commercial applications in the hospitality and tourism field are flourishing. The following section provides an overview of how this research reviewed the publication within hospitality, tourism, and restaurant food-related fields by segmenting into important time points and in-depth look at methods.

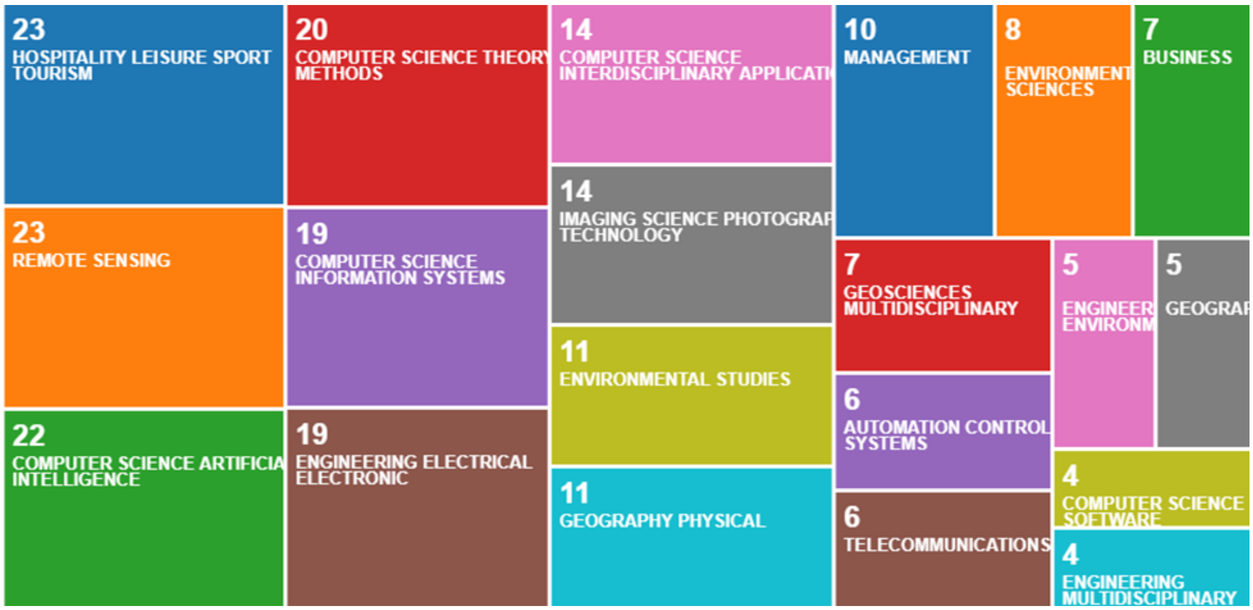
3. Methodology

3.1. Literature search

A collection of the relevant literature on image analysis on deep learning used in hospitality and tourism was extracted from both Web of Science (WOS) and 124 hospitality and tourism journals listed in SJR (Scientific Journal Rankings). For WOS and hospitality tourism journals search, the keywords search terms included: ("image analysis" or "photo analysis" or "visual information" or "visual analysis" or "object detection") AND ("deep learning" or "machine learning") AND ("tourism" or "tourism environment" or "destination marketing" or "hospitality" or "attractions" or "restaurant food"). In 124 hospitality and tourism journals, the keyword search terms included: ("image analysis" or "photo analysis" or "visual information" or "visual analysis" or "object detection") AND ("deep learning" or "machine learning").

An overview of relevant literature after the query from WOS included 125 results, with 30 conference proceedings, 19 book chapters, and 76 journal articles. The tree-map in **Figure 1** explicitly displays the field of published journals, with 23 in the hospitality/leisure/sport/tourism category, 23 in remote sensing, and 22 in computer science artificial intelligence.

Figure 1-1 **Tree map of papers categories**



From conference proceedings, the top 10 articles ordered by citation rank are presented in **table 1.**

Table 1-1 **Top 10 Journal articles on WOS ordered by citation score.**

Journals title	Year	Authors	Source	2017	2018	2019	2020	2021
Exploring the travel behaviors of inbound tourists to Hong Kong using geotagged photos	2015	(Vu et al., 2015)	Tourism Management	22	25	28	50	15
Effects of user-provided photos on hotel review helpfulness: An analytical approach with deep leaning	2018	(Ma et al., 2018)	International Journal of Hospitality Management			19	25	15

Discovering the tourists' behaviors and perceptions in a tourism destination by analyzing photos' visual content with a computer deep learning model: The case of Beijing	2019	(Zhang et al., 2019)	Tourism Management			2	18	14
Using social media to identify tourism attractiveness in six Italian cities	2019	(Giglio et al., 2019)	Tourism Management			6	15	10
Road-based travel recommendation using geo-tagged images	2015	(Sun et al., 2015)	Computers Environment and Urban Systems	8	11	12	12	3
Designing tourist experiences amidst air pollution: A spatial analytical approach using social media	2020	(Xiaowei Zhang et al., 2020)	Annals of Tourism Research				2	4
Learning patterns of tourist movement and photography from geotagged photos at archaeological heritage sites in Cuzco, Peru	2021	(Payntar et al., 2021)	Tourism Management					2
Understanding tourists' urban	2020	(Kim et al., 2020)	Heliyon				1	2

images with geotagged photos using convolutional neural networks								
How are Tourists Different? - Reading Geo-tagged Photos through a Deep Learning Model	2020	(K. Zhang, D. Chen, et al., 2020)	Journal of Quality Assurance In Hospitality & Tourism				2	1
Forecasting with time series imaging	2020	(Li et al., 2020)	Expert Systems with Applications				1	

Table 1-2 **Top 10 conference proceedings on WOS ordered by citation score.**

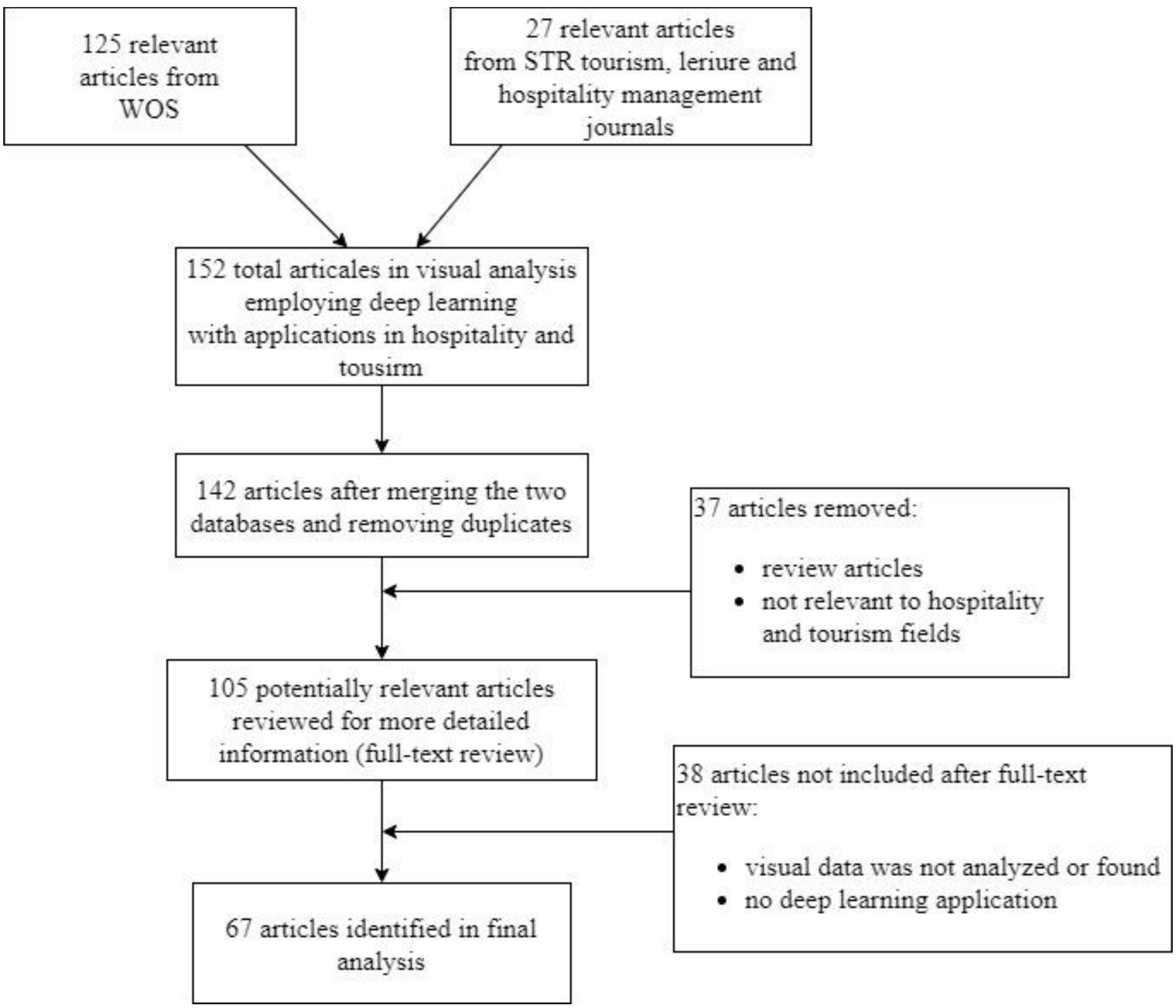
conference article title	Year	Authors	Source	2017	2018	2019	2020	2021
Image-Based Food Calorie Estimation Using Knowledge on Food Categories, Ingredients and Cooking Directions	2017	(Ege & Yanai, 2017)	Proceedings Of the Thematic Workshops of ACM Multimedia 2017 (Thematic Workshops'17)	0	1	9	3	0

An end-to-end deep neural architecture for optical character verification and recognition in retail food packaging	2018	(Ribeiro et al., 2018)	2018 25th IEEE International Conference On Image Processing (Icip)	0	0	4	3	2
Image-Based Food Calorie Estimation Using Recipe Information	2018	(Ege & Yanai, 2018)	IEICE Transactions On Information and Systems	0	0	5	1	2
FooDD: Food Detection Dataset for Calorie Measurement Using Food Images Image-Based Food Calorie Estimation Using Recipe Information	2015	(Pouladzadeh et al., 2015)	New Trends in Image Analysis And Processing - ICIAP 2015 Workshops	6	1	3	2	0
Discovering Tourists' Perception About Food by AI and NI	2020	(K. Zhang, H. Wang, et al., 2020)	Tourism Product Development in China, Asian and European Countries	0	0	0	0	1
A Method of Modeling of Basic Big Data Analysis for Korean Medical Tourism: A Machine Learning	2017	(Huh et al., 2017)	Information Science and Applications 2017, ICISA 2017	1	0	1	0	0

Approach Using Apriori Algorithm								
Comparison of Supervised Learning Image Classification Algorithms for Food and Non-Food Objects	2018	(Yogaswara & Wibawa, 2018)	2018 International Conference on Computer Engineering, Network and Intelligent Multimedia (CENIM)	0	0	0	1	0
A Food Photography App with Image Recognition for Thai Food	2018	(Tiankaew et al., 2018)	2018 Seventh ICT International Student Project Conference (ICT-ISPC)	0	0	0	1	0
Integrating machine learning techniques and high-resolution imagery to generate GIS-ready information for urban water consumption studies	2012	(Wolf & Hof, 2012)	Earth Resources And Environmental Remote Sensing/GIS Applications III	0	0	0	2	0

WOS citation score is calculated using the number of citations over time. Most of included papers have a low in-degree score as a result of being recent publications. To gain meaningful insights into visual information analysis publications, potentially relevant publications were carefully reviewed. First, only English-written papers were considered. From the keywords search in tourism and hospitality journals, 27 relevant articles were listed. In the WOS search, 125 relevant articles were identified. Second, the researchers combined both datasets and removed duplicates, which left 142 articles after merging. After reviewing the abstracts, 37 articles were removed due to lack of relevancy to the field. Third, 105 potentially relevant articles were reviewed at full-text length for further filtering. After reviewing the full-text, 67 articles were selected for the final papers, and 38 articles were not included due to lack of visual data and absence of deep learning for visual data analysis. **Figure 2** demonstrates the process of refining the selection of the papers.

Figure 1-2 **Process of refining selection of final papers**



3.2. Citation network analysis

Citation networks are commonly used to examine citations in documents and identify the most connected documents in a collection (Greenberg, 2009). In this study, references from all 67 papers were extracted to perform citation network analysis and further explore the relationships of the selected studies. Gephi software was used to perform citation network analysis and statistics indicating centrality of the correlated papers. The edge table was created with the authors' names in APA style, followed by the article publication year. Citations that were not in APA format were manually changed into APA format for analysis. Therefore, all citations were unified to avoid confusion. In addition, the researchers identified articles with the same group of authors and published in the same year from the article dataset. Then renamed the identified articles with "a" and "b" to categorize them. Only academic papers references were considered; the web sources' references were excluded. The final direct graph consisted of 3,236 nodes (papers) and 3,501 edges (citation links). In addition, betweenness centrality and eigenvector centrality were calculated to rank the influences of individual papers in the citation network. Betweenness centrality measurement is a way to find nodes that serve as bridges and reveal the shortest paths in the network. Eigenvector centrality assigns relative scores to all nodes in the network based on connections to high-scoring nodes indicating strong influence. Therefore, both are used as measures to identify well-connected papers.

3.3. Text clustering analysis

Text clustering has been studied extensively for its use in generating clusters of text data that share similar characteristics. The statistical analysis of term (word or phrase) frequency is used to capture the importance of terms within a document and form semantics (Shehata et al., 2006). SAS Enterprise miner was used for data pre-processing and text clustering analysis. From all the selected papers, abstract data was analyzed. First, all text was converted into lower case, and stop words, numbers, punctuation, and part of speech (conjunction, determiner, pronoun) were removed. The remaining text was tokenized, and Porter's stemming algorithm was applied to perform stemming (Porter, 1980). Furthermore, the log frequency weighting method and entropy term weighting methods were applied (SAS Institute Inc., 2011; Wang et al., 2015). At last, for text clustering, the expectation-maximization (EM) algorithm was used (Bradley et al., 1998). An iterative approach was utilized to stop the algorithm with non-overlap criteria. Finally, seven different clusters of abstract semantics with distinguishing features were identified.

4. Results

4.1. Current state of hospitality and tourism literature in machine learning application on visual analysis

4.1.1. Longitudinal overview of studies on visual analysis in hospitality tourism field

From 2012 to 2015, discussions on machine learning applications for analyzing image data in the hospitality and tourism field took place mostly outside of hospitality and tourism journals. In 2012, LDAHash improved feature descriptors which improved content-based retrieval, particularly affine and intensity scale transformations. These benefited photo tourism, object recognition, and related image analysis (Strecha et al., 2011). Soon after, location-based tourism information outlined tourists' personal interests. By analyzing both textual and geotagged photo data, the results were used to predict attractions and provide recommendations (Vu et al., 2015). From the studies' findings, geo-based technology was confirmed to enable people to be more knowledgeable about destinations and to make spatial-related decisions (Tussyadiah & Zach, 2012). In addition, users' preferences and travel behaviors, combined with temporal and geographic features of photos, and further classification of the photos, can indicate attraction popularity, (Jiang et al., 2013; Zhou et al., 2015).

From 2016 to 2018, although the literature still mainly focused on tourism and destinations, the parameters of tourism became more specific, such as inbound tourism (Gupta et al., 2018; Su et al., 2016) and culture tourism (Wang et al., 2018). Discussions on tourism behavior patterns using geotagged photos continued, but with a more advanced analytical framework that extended the concept of network motifs to further quantify user similarity based on semantic travel motifs (Yang et al., 2017). In addition, hotel photos and reviews received attention. (Ma et al., 2018) suggested photos alone do not provide sufficient cues for decision making, and the combination of online review and user-generated photos reinforced the effects of review. Moreover, food attribute exploration and multimodality content were considered in algorithms in the food domain (Min et al., 2016).

From January 2019 to June 2021, the number of articles greatly increased. the discussion on features extracted through photos aimed to understand tourism behaviors and increase rigor of exploration. Image data's features including color, objects in the image, and geo-location were explored and combined for a more extensive evaluation (Arefieva et al., 2021; Bui, 2021; Yim et al., 2021). Compared to previous years, more diverse tourism areas were included, such as tourism environmental impact and tourism risk management. Similarly, in the hotel domain, classifications between hotel-generated photos and user-generated photos were analyzed for purposes such as hotel marketing, branding, and feature comparison (Giglio et al., 2020; Li et al., 2021; Ren et al., 2021). Comparatively, in the food and restaurant-related domain, restaurant recommendations and food recognition informs implications on the consumer decision-making process (Jiang et al., 2020; Xiaoyan Zhang et al., 2020). In addition, data sources were diversified, and researchers tended to use social media data, such as TripAdvisor, Instagram, etc.

The distribution of papers per year is demonstrated in **figure 3,** and **figure 4** displays the articles' area distribution.

Figure 1-3 **Number of papers per year**

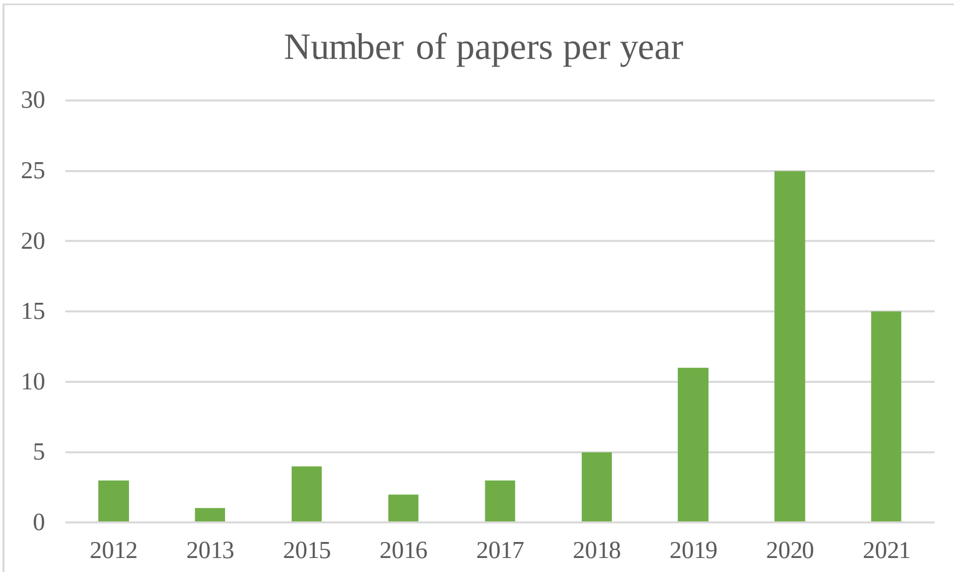
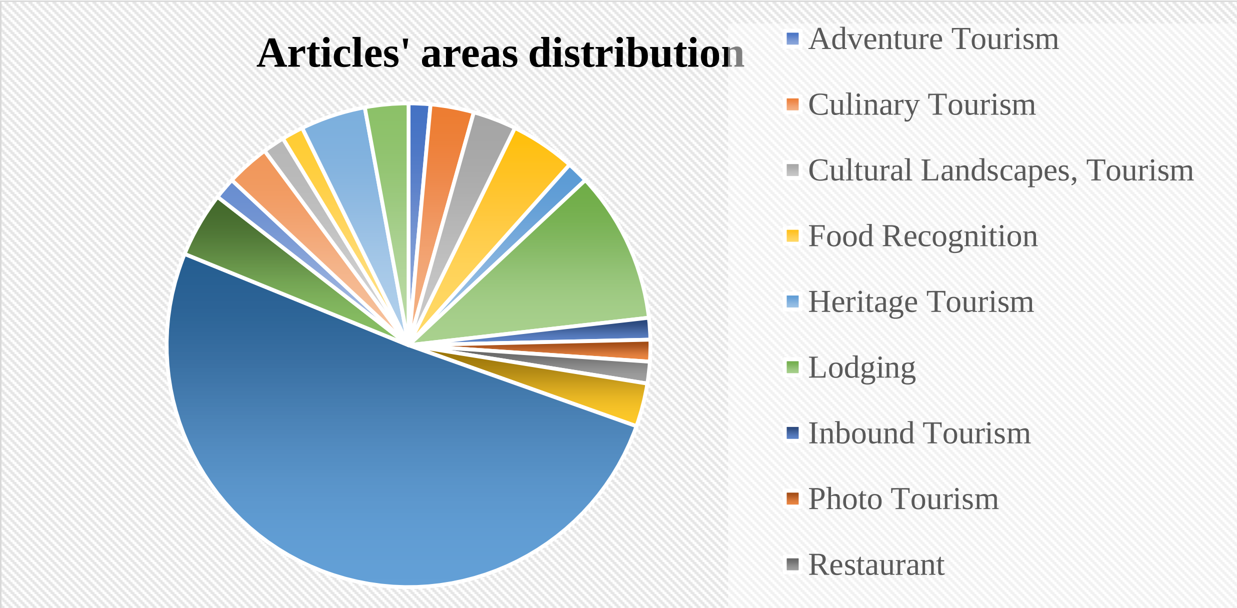


***Figure 1-4* Articles' areas distribution.**



4.1.2. An in-depth look at approaches

All the advancement and improvement in deep learning algorithms and methods for computer vision are preparing academia and businesses with better tools to solve real-life problems. Therefore, understanding applications can further guide an algorithm's advancement. In academia, the applications of algorithms tend to fall into three broad categories:

- function approximation, including time series prediction and modeling;
- image classification, including pattern and sequence recognition, and novelty detection;
- data processing, including filtering, clustering, and compression.

Similarly, in the tourism and hospitality field, the literature identified three common deep learning application methods for tourism image studies: (1) prediction modeling using geographical information, combined with user-contributed geotagged photos to perform spatial analysis, and to identify popular traveling spots and travel recommendations and predict tourist arrivals; (2) image aesthetic and color analysis basis on the fundamentals of color theory; (3) object detection analysis by adopting existing API (Application Programming Interface).

Overall, the aims for tourism and hospitality image studies were mostly exploratorily, uncovering patterns and attributes and understanding how tourists associated their experiences or engaged with social media.

Geographic information and geotagged photos are available on photo-sharing websites, such as Flickr and Panoramio. The advent of location-aware technology equipped mobile devices with GPS chips and embeded geographical information when taking photos. The analyses for geotagged photos mostly involved more than one method. The increasing number of geo-tagged photos provides opportunities for clustering analysis and spatial analysis[1], and it even generates internal paths in tourism attractions, including the estimation of time spent to further recommend or predict demand (Jiang et al., 2013; Sun et al., 2015; Tussyadiah & Zach, 2012; Vu et al., 2015; Zhou et al., 2015). Recommendations based on personal interests, spatial analysis results, and further advanced network are able to provide a more accurate prediction of travel interests (Yang et al., 2017).

Image aesthetic and color analysis based on the fundamentals of color theory mainly focuses on the perception of color and its psychology influences. Image annotation and clustering are mostly achieved by applying pre-existing API, such as Google Cloud Vision. Using term frequency counts on image labels, inter-cluster and image-network-graphs further cluster the highly connected images. Furthermore, engagement data from social media can further verify and support evaluation of aesthetic and color theory in tourism (Arefieva et al., 2021). Therefore, color analysis is an important consideration for photo tourism researchers to extract and summarize heterogenous elements to interpret topics.

[1] Spatial analysis: seeks to explain patterns of human behavior; clustering: define and group attractions in tourism literature.

Object detection analysis utilizing existing APIs was the most common approach in the literature for feature extraction. Normally, multiple labels can be detected to identify general objects, locations, activities, animal species, products, and text (Nanne et al., 2020). These detected labels can further analyze and classify into different topic models. It is a way to explore the meaning behind an image. Word2Vec model and term frequency-inverse document frequency (tf-idf) were commonly seen when classifying detected labels and text descriptions (Arefieva et al., 2021; Giglio et al., 2020; Sheng et al., 2020). Improved algorithms primarily increased image recognition accuracy and processing speed. Therefore, the existing APIs achieved a satisfactory accuracy and processing speed when generating image data output. This approach was commonly seen in cross-discipline studies outside of computer science. In addition, many studies used a combination of approaches for a comprehensive understanding on specific topics. In addition, it was common to see studies use a combination of textual data and image data or data from multiple sources for a rigorous discussion of reliability and validity.

4.2. Citation network results

Results showed that papers written by (Vu et al., 2015) and (Su et al., 2016) displayed the highest betweenness centrality score in the network. These two papers discussed how geotagged photos could reveal tourism behavior and geographical preferences. In addition, these two papers utilized social media data from Flickr to examine tourism behaviors across time and space. These two papers were published only a year apart. Therefore, it is not surprising to see the stronger linkage between these two papers and the rest. Table 3 shows the top 10 papers sorted by betweenness centrality. Both in-degree and out-degree are reported, in which the in-degree score refers to the number of papers directing to the original study, and the out-degree scores indicate the number of papers being cited in the citation network.

Table 1-3 **Top 10 papers in terms of betweenness centrality score.**

Top 10 connected papers	Eigen centrality	In degree	Out degree	Betweenness centrality	Journal
(Vu et al., 2015)	0.35	10	43	452.75	Tourism Management
(Su et al., 2016)	0.05	5	52	448.50	Applied Geography
(Sun et al., 2015)	0.20	7	40	382.58	Environment and Urban Systems
(Zhou et al., 2015)	0.17	4	37	269.42	Computers, Environment and Urban Systems
(Deng & Li, 2018)	0.05	5	49	236.00	Tourism Management
(Jiang et al., 2013)	0.12	3	22	110.67	Neurocomputing
(Ma et al., 2018)	0.01	1	78	75.00	International Journal of Hospitality Management
(Giglio et al., 2019)	0.02	2	21	72.00	Tourism management
(Peng & Huang, 2017)	0.02	2	27	54.08	ISPRS International Journal of Geo-Information
(Samany, 2019)	0.01	1	50	43.00	Cities

From identified papers, modularity optimization was performed to detect communities in the network. The randomized optimization was tested under three resolution levels: 0.25, 0.5, and 1. After running under three levels, resolution 1 got a manageable number of communities without having too large of clusters, with modularity of 0.894. It produced 36 communities. The selection was based on the highest modularity score, where resolution at 0.5 had modularity at 0.890 with 42 identified communities, and resolution at 0.25 had modularity at 0.891, with 46 identified communities. Similarly, this rule was applied in (Loureiro et al., 2020) study to select the appropriate resolution. From the top 10 communities in the network, it represented 42.61% of the total 36 communities. Table 4 shows the 10 most representative communities, numbers of papers in each community, its most connected papers from each community, and in-degree, out-degree scores. Some papers featured low-degree scores due to being recent publications.

Table 1-4 **Top 10 communities of papers.**

Cluster	%	# Papers	Most connected papers	In-degree	Out-degree
1	8.75	283	(Vu et al., 2015)	10	43
2	5.19	168	(Su et al., 2016)	5	52
3	4.94	160	(Zhou et al., 2015)	4	37
4	5.22	159	(Giglio et al., 2019)	2	21
5	4.94	128	(Deng & Li, 2018)	5	49
6	4.91	90	(Ma et al., 2018)	1	78
7	2.60	84	(Arefieva et al., 2021)	0	89
8	2.38	77	(Yim et al., 2021)	2	0
9	1.98	64	(Barnes & Kirshner, 2021)	0	64
10	1.70	55	(Peng & Huang, 2017)	2	0

Cluster 1 group papers that were used to understand tourists' behavior based on the role geo-tagged photos played in travel. Cluster 2 groups papers focused on influential factors on destination preferences using geo-tagged photos. Cluster 3 groups papers detecting tourism destinations, travel experiences and preferences. Cluster 4 has a community of papers on measuring attractiveness in a region around the work of Giglio et al. (2019). Cluster 5 groups papers relevant to photo selection for destination marketing around the work of (Deng & Li, 2018). Cluster 6 includes papers on photo usage to provide feedback around the work of Ma et al. (2018). Cluster 7 groups papers with a discussion on clustering destination images with photos. Cluster 8 contains papers discussing the travel photos effect. Cluster 9 groups papers with facial image analytics. Cluster 10 includes papers about discovering attractive tourism destinations.

Figure 5 shows the graph with original papers and their connected citations. The top 10 papers were labeled in the visualization for better interpretation.

Figure 1-5 **Citation network with top 10 papers labeled.**

4.3. Text clustering review in selected literature

Seven paper clusters were identified from the selected literature and are discussed in detail in this section. Based on the topic terms frequency in each cluster, topics were formed, and papers that fell into the same cluster were identified. Table 5 includes each topic's name, topic terms, number of papers in the topic, and identify ones with a higher correlation with the topic terms. All the topics are discussed in the following section.

Table 1-5 **Clustering topics for papers**

Topics	Topic terms	# Papers in the topic	Correlated paper with the topic
1. Scene identification incorporating artificial intelligence (AI) for tourism destinations	+technology +destination +development +approach +artificial +intelligence +computer +tourist +scene +identification +sample +small +big +data +effective +explore +deep +features +tourism +advancement	10	(Wang et al., 2020)
2. Social media marketing in hospitality and tourism	+consumer +review +practical +implication +user +online +literature +marketing + practical +mining +experience +content +post +recognition + social +media +visual +purpose +algorithm +application	9	(Giglio et al., 2020)
3. Assess location based geo-tagged photos	+urban +design +implement +view +perspective +method +environment +geo-tag +propose +accuracy +assessment +employ +extract +investigate +tourism +perception +activity +case +location +visual	9	(Xiaowei Zhang et al., 2020)
4. City images and protective measures	+area +characteristic +detection +cultural +grow +involve +activity +element +category +detect +difference +face +increase +attraction +classify +integrate +large +city +risk +management	6	(Sambolek & Ivasic-Kos, 2021)

5. Image recognition in food	+food +system +food +improve +focus +problem +classification +feature +technique +recognition +application +combine +play +learn +visual +deep +classify +design +network +accuracy	11	(Min et al., 2016)
6. Cultural ecosystem services (CES) and photos aesthetic	+cultural +visitor +aesthetic +region +natural +service +highly +present +site +develop +ecosystem +photograph +landscape +model +find +value +important +role +case +place	8	(Gosal & Ziv, 2020)
7. Recommendation system	+recommendation +preference +movement +travel +location +attraction +time +cluster +interest +people +reserve +right +novel +user +detect +represent +behavior +apply +system +effective	14	(Xiaoyan Zhang et al., 2020)

Topic 1. Scene identification incorporating artificial intelligence (AI) for tourism destinations.

With the development of advanced technologies, the tourism industry is facing a more intelligent and automated environment. Online destination photos deliver great benefits for understanding projected destination images and further enhancing tourism experiences. Wang et al. (2020) identified 25 image scene identification from the tourism destinations and established an artificial intelligence model combining a deep convolutional neural network with transfer learning to achieve peak model performance. Thus, destination image studies are no longer limited by questionnaire surveys (K. Zhang, D. Chen, et al., 2020). Scene identification can work with a massive number of tourists photos, and it breaks the limitations of manual approaches. From Xiao et al. (2020)'s study, 365 scenes were identified through deep learning technology, which further contributed to scene identification for tourism destinations. By categorizing the tourism scene, the outcome of visual content mining on travel photos makes it possible to understand tourism destination images and uses pictorial pieces of evidence to tourism marketing (K. Zhang, Y. Chen, et al., 2020). Thus, Topic 1 explores scene identification for tourism photos, which may inform tourists' behaviors, travel patterns, and tourists' preferences. Moreover, the AI photo identification framework used relevant visual data and contributed to forming projected online destination images (Xiao et al., 2020; K. Zhang, Y. Chen, et al., 2020).

Topic 2. Social media marketing in hospitality and tourism

Topic 2 presents literature focused on marketing using social media photos. In He et al. (2021)'s study, both destination marketing organizations and UGC visual information were employed to project a selection for the "right" image. The findings suggested photos that match consumers' central impressions induced higher online engagement. Similarly, in the hotel setting, Giglio et al. (2020) analyzed TripAdvisor consumer posted photos which lead to the identification of attributes that had a higher impact on luxury hotel brand perceptions and experiences. In a restaurant setting, Hasan et al. (2020) explored restaurants' photos on TripAdvisor and clustered 12 hierarchical image categories. Subsequently, the study used exploratory survey and investigated consumers' purchasing behavior and sharing motives, which evaluates the effectiveness of social media marketing in restaurants.

Topic 3. Assess locations based geo-tagged photos

Geo-tagged photos are widely used for visual data and analyzed in hospitality and tourism literature. K. Zhang, D. Chen, et al. (2020) collected geo-tagged photos from 18 cities to explore place-informative scenes by applying a deep convolutional neural network. The study identified distinctive visual cues of each city, including landmarks, historical architecture, unique urban scenes, and unusual nature landscapes. The study provides insight into understanding place image formalization. In addition, geo-tagged photos were utilized to understand tourists' behaviors. In Vu et al. (2015)'s study, travel patterns and tourists' movement paths were revealed from spatial and temporal information in photos. Moreover, location-based tourism images can exploit effective spatial cognition and enhance the identification of geographic locations (Lee & Wang, 2012). In Chen et al. (2019)'s study, geo-tagged metadata were applied to predict inbound tourism flows in cities, thus, providing a novel method to forecast inbound tourists flow.

Topic 4. City images and protective measures

Topic 4 addresses maintaining city images and identifying crises from visual information are effective for regional development. Taecharungroj and Mathayomchan (2021) selected 222 cities to study city image dimensions (CIDs). From the findings, the study identified both universal CIDs and individual CIDs to highlight city brandings and marketing strategies. Universal CIDs included cityscape, landscape, transport, architecture, and recreation. However, not all destinations have positive destination images as tourism destinations. Identifying challenges can help restore and protect the scenic areas. Protective measures are often discussed in the literature. Wang et al. (2019) analyzed geotagged photos from Beijing's historic areas and found that cultural heritage received little attention and needs to be protected by emphasizing emerging tourism and business activities. Additionally, Zhu et al. (2020) addressed the necessity of vegetation protection measures at tourism facilities in Nanjing, China, by utilizing image data to quantify vegetation changes at a national scenic location. The study proposed that local government should take action and raise awareness of sustainability needs. Similarly, Wang et al. (2018) found the Great Wall in Beijing facing a crisis of fragmentation that could affect natural geography environments, which is associated with historical heritage. Unfortunately, there is a lack of attention on cultural landscapes. Moreover, an interesting aspect of protective measures for adventure tourism was proposed by Sambolek and Ivasic-Kos (2021). The study established a person detection model to increase the search effectiveness in a large territory, and aimed to provide assistance to rescue operations while minimizing the damage.

Topic 5. Image recognition in food

Food images are often valued for many aspects, such as visible ingredients, nutrition perceptions, and taste perceptions. To address some of the aspects, Min et al. (2016) proposed a multimodal multitask deep belief network to learn more from food images. The model can identify cuisine, ingredients, and dish types to derive deep features of the food images. The features can further support dietary assessment and even be used for food journaling. Similarly, Jiang et al. (2020) proposed a multi-view, few-shot learning framework as an updated food image recognition model. Introducing ingredient information into the networks can improve the model performance and bridge the gap between the training set and the testing set. The model addressed the problem of existing works focusing on food recognition through labeled samples and unsuccessful recognition of food categories with few data points.

Topic 6. Cultural ecosystem services (CES) and photos aesthetic

The term cultural ecosystem services (CES) refers to the non-material benefits people obtain from the environment, heritage values, and cultural identities, such as aesthetic appreciation of natural landscapes, recreation, and tourism (Hassan et al., 2005). This topic contains literature that studies CES in a photo aesthetic setting. Fung and Jim (2015) explored visitors' perceptions of geo-heritage and associated natural and cultural aspects of visitor-employed photography to uncover the necessities of protecting significant geo-heritage features. The findings also demonstrated that visitors develop strong emotional connections with nature through appreciating and learning about prominent features from CES. Gosal and Ziv (2020) studied the Yorkshire Dales National Park region by utilizing publicly available images and text annotations to develop a spatial model to predict and map landscape aesthetic value across the site. The findings demonstrated the positive role of rural areas, mountainous landscapes, and vegetation in adding aesthetic value. In addition, Ghermandi et al. (2020) expanded the idea by investigating cultural services accessed by local, domestic and international visitors. The study found locals were more likely to be associated with aesthetic appreciation of nature and uploaded more photographs that contained nature content.

Topic 7. Recommendation system

A recommendation system is often associated with combining explicit quantitative feedback and user expressed preferences to give final recommendation results. In this topic, a cluster of papers incorporated photos' textual and visual information to reveal users' personal interests. In Xiaoyan Zhang et al. (2020) 's study, the multi-view visual featured recommendation systems that have been developed to assess consumers' preferences for restaurants. Experimental results indicated that the model with multi-view visual information achieved better performance than models without or with single-view visual information. This validates the important role that visual information plays in consumer selection and decision making.

Moreover, the tourism recommendation system is discussed in depth in the selected literature. Points of interest (POIs) can be identified from photo geo-locations, where social media plays a primary role in the recommendation process (Giglio et al., 2020). Since the recommendation system is not built on solo factors, Jiang et al. (2013) evaluated tourism attractions' popularity with photo textual and visual information, and spatial influences on users' personal interests were considered. The method predicted users' preferences from different perspectives and combined the prediction scores to provide a final recommendation. Similarly, Yang et al. (2017) suggested establishing an effective tourism recommendation system, found that typical tourist travel behavior patterns are critical to identify, and determined that the travel patterns are associated with distinctive preferences. Furthermore, Kolahkaj et al. (2020)'s study generated dynamic recommendations by considering time, location, ratings, tourism sequential travel movement patterns, and tourist characteristics. By utilizing geotagged photos, the system recommended travel packages, predicted POIs, and improved the recommendation system by proposing a hybrid context-aware approach.

5. Avenues for future research

As visual information such as photos, continues to make an impact on people's daily life, and methods of analyzing image metadata continue to advance, it is foreseeable that applications of image recognition and analysis will benefit the hospitality and tourism industry, as well as academia. Technological interfaces on image recognition, such as facial recognition, have already been widely applied in the hospitality and tourism industry. Subsequently, academic research is seeing growth on visual information analysis and extraction of deep features from the image data. Researchers are working on improving image recognition models by adding more categories, using an additional number of labeled photos for training and testing, and seeking a way to incorporate unsupervised machine learning.

Today, social media platforms have the ability to share visual information in both photo and short video formats. New social media video-sharing platforms, such as TikTok, have quickly gained popularity and been downloaded over 2.6 billion times worldwide (Leskin, 2020). The popularity of short video sharing platforms corresponds with research findings that videos have higher user engagement on social media (Khan, 2017). With the popularity of occupations, such as online travel bloggers, lifestyle bloggers, and food bloggers, social media's marketing influence on the hospitality and tourism industry is not to be underestimated. Hence, as an overview of the past literature in analyzing a large quantity of visual information data employing machine learning techniques, data sources are mostly social media photos and are problem-based. Such papers highlight some important future research topics are displayed in Table 6.

As thoughts for the future evolution of visual information analysis in tourism and hospitality, four key realms are envisioned to explore more on visual information in the hospitality and tourism field:

1. incorporate videos as visual information data;
2. enhance and improve image recognition models by adding more categories, and incorporate more labeled image data to achieve better model performance;
3. integrate exploratory studies to expand and validate consumers' preferences;
4. study and triangulate tourism movement patterns and triangulate data for deeper features.

Table 1-6 **Research questions and future topics on visual information for hospitality and tourism.**

Research questions	Future topics	Authors
How do the subjective interpretive dimensions of photos influence user engagements on an online travel review site?	Compare stand-alone photos with photos taken by consumers on the move for aesthetic quality and memory-binding effects on users. Develop more specific findings that are integral to business impact. Investigate other variables that can affect user engagement and include consumers' mobility.	(Yim et al., 2021)
the research question in this paper is structured as prepurchasing and postpurchasing consumer behavior on social networks in culinary tourism.	Choose other tourism locations and on assorted review platforms to investigate the possibility of identifying different types of tourist behavior. Video content, animations and stories would be useful for a wider	(Hasan et al., 2020)

	understanding of tourists who use the internet. Study tourist behavior with additional online post variables.	
What do tourists notice at the sites and consider worthwhile to photograph and post online? Do tourist images converge around a set of canonical views, some of which were first introduced to popular media more than a century ago? To answer these questions, we quantify the contents of discovered canonical views per site	Examining how tourist scene-captures have evolved over time. Studying movement patterns and hotspots within heritage sites and identifying outlier archaeological sites 'on-the-rise' through social media platforms.	(Payntar et al., 2021)
this research seeks to address the following question: With the increase of the presence of AI in the tourism field, can an AI framework of destination photo identification be developed for better marketing decision-making?	Multi-object tourism photo identification. Semantic segmentation of destination images via the use of deep learning.	(Wang et al., 2020)
How can big data analytics and machine learning algorithms help monitoring social media and understand consumers' perception of luxury hotels? How can big data analytics turn into better brand management strategies for luxury hotel managers?	Build a larger data set with hotels in other cities with similar characteristics. Investigate emerging elements in budget hotels. Triangulate the data with information about the duration of the vacation.	(Giglio et al., 2020)
how to effectively apply computer vision technology into tourists' behaviors and perception analysis in the field of tourism destination study	Address the usage of AI as a viable and necessary part for the operations.	(Zhang et al., 2019)

What are the constituent elements of locality for Beijing’s historic areas? How does one classify historic areas according to locality elements? What are the characteristics of each kind of historic area? How does one identify to-be-protected locality elements according to different historic areas to realize sustainable development?	Add classification of locality elements under same method to address future protection and renewal activities in historic areas	(Wang et al., 2019)
To initiate the discovery of this novel research theme, a crucial question should be answered first. How does a business design an effective cover photograph?	Examine cover photographs on OTAs with the focus of hotels. Test findings in experimental setting. Reexamine the model for different classes of the offerings, eye-tracking experiments are highly recommended to investigate the relationship between the themes of cover photographs and further information search behavior on OTAs.	(Luo et al., 2021)
What impact does the perceived trustworthiness and attractiveness of a host garnered from their profile photo have on the price of online accommodation, and how does this vary by accommodation type?	Leverage an alternative and larger-scale training dataset to classify faces on a more detailed scale. Look at the impact of power/dominance and its potential interaction with valence/trustworthiness on prices in Airbnb. Develop mechanisms that can capture true trustworthiness and attractiveness, incorporating these factors into platforms like Airbnb to determine their impact on pricing.	(Barnes & Kirshner, 2021)
What is the influence of the internet and the destination projected by traveler-generated photos?	Compare the results of new method with those of traditional methods, such as survey. Explore several techniques to compare and contrast the outcomes. An examination of smaller and lower-tier cities may generate different results.	(Taecharungroj & Mathayomchan, 2021)

Figure 6 shows the main topics evolution around the discussion of visual information in tourism and hospitality in the future.

Figure 1-6 Main topics evolution

6. Conclusions

Visual information and machine learning techniques are creating endless possibilities for the hospitality and tourism field. It has been applied in operating, educating, marketing, and transforming consumers' experiences, as well as helping researchers identify features and issues of tourism destinations. Many research aspects have been addressed in the cited literature on understanding visual information employing data analytic tools, such as discovering tourism travel patterns, forecasting tourism flows, exploring consumer preferences, and understanding destination image formation. More and more discussions are being formulated on the importance of incorporating visual information in research and data triangulation from various sources, considering different factors. With the advancement of image recognition algorithms, higher accuracy and better performance will be achieved.

This study first discussed the overall research that has been conducted over time on visual information analysis applying machine learning techniques in hospitality and tourism disciplines and introduced the evolution of machine learning algorithms. Second, citation network analysis of the identified literature and references were conducted to reveal influential papers. Third, the this study used a text mining technique to identify topics through applied text clustering analysis. To add depth and rigor to the study, the results included a longitudinal overview of identified papers and elaborated on data analytic approaches in the existing literature. This section aims to expand the discussion on machine learning methods for visual information analysis. A citation network specified 10 communities with majority papers, whereas text clustering results identified 7 topics. This discrepancy was due to the similarity of clusters 1 and 2, which both referenced geo-tagged photos. Similarly, cluster 5 and cluster 10 shared a similar topic, understanding social media marketing. In the identified topics, CES and photos aesthetic were considered as one topic. Although CES has a broader definition and greater meaning than photo aesthetic, in hospitality and tourism visual information literature, CES is always discussed as aesthetic appreciation for surroundings, including cultural heritage and nature. Importantly, consumers' destination images can be evaluated from UGC, and the discussion on destination image is no longer limited to survey data. Furthermore, the negativity of consumers' destination image can also be evaluated by incorporating satellite images and geo-tagged photos and by conducting time-series studies.

This study helps researchers understand the main topics discussed so far in the literature and become more familiar with analytical approaches so that future research may expand on each identified topic and focus on what has not been done. Findings may also be used as an overview of the current stage of visual information literature applying machine learning and future directions for algorithm improvement.

Chapter 2 Standing out from the crowd: exploring online information cues on Airbnb gastronomy experiences

1. Introduction

1.Introduction

With the rising of sharing economy travel marketplace, online peer to peer (P2P) platforms such as Airbnb have been at the center of discussions among scholars and practitioners due to their impact on the hospitality industry and the fast speed of growth as a business (Dogru et al., 2019; Sigala, 2017). The discussions are mostly surrounded the accommodation services and how online platforms are revolutionizing the lodging market (Dogru et al., 2019; Mody et al., 2017). However, little attention has been spent on "experiences" provided by these platforms, which are directly related to the gastronomy tourisms. The major players such as Airbnb recognized the potential of gastronomy experiences and carved out a category as "food and drink" experiences where more than 3,000 experiences are exclusively dedicated to the gastronomy worldwide. Among all the experiences, this category is the most booked and has grown 160 percent since 2018 (Ting, 2019). A fast-growing category of tourism like gastronomy creates a competitive environment for the online platforms, and the transparency of web information endangers uniqueness and innovative experiences. How to stand out from the listings and what information cues consumers value more when searching the gastronomy experiences remain uncovered. Therefore, this study focuses on consumers' information processing, aiming to elaborate tourists' selections based on information cues displayed through online platforms.

First, this study aims to investigate information cues displayed through Search Engine Result Page (SERP) (we use Airbnb as a context in this study), including promotional photo cues, numbers of reviews, ratings, average time spent, price. In addition, we also focus on the role of host credibility on customer decision making. Host credibility has been discussed in the previous literature as an important consideration for tourists' product selection through a sharing economy platform, such as Airbnb (Ert et al., 2016; Ma et al., 2017). The perceived trustworthiness of host profiles was studied from different dimensions: host headshots (Barnes & Kirshner, 2021), profile length, profile themes (Ma et al., 2017), and how trustworthiness impacts prices (Tong & Gunter, 2020). To our best knowledge, the incorporation of host credibility has never been explored from a consumer decision making phase with consideration of various information cues presenting at the same time. In addition, image has long been discussed as one of the key determinators for people making decision, especially for food related products (Lai et al., 2018; Mak et al., 2017). Hence, factors that might potentially influence the consumers' decisions are considered in our research.

Secondly, there have been concerns raised about website information overload (Chen, 2018; Li, 2017; Sthapit et al., 2019). People process information online differently. To further explore the differences, this study adopts the heuristic-systematic model (Chaiken, 1980; Eagly & Chaiken, 1993) and signaling theory as the theoretical foundation to explain tourists' information processing and identify the mechanism of displayed information cues on an online P2P platform at discrete levels, and learn how tourists make selections. As such, to be able to assess the effects in a valid way, this study simulates Airbnb SERP and segments information cues based on web collected data using the principle of math quartile for price, ratings, reviews, and estimated time spent. In addition, the thematic categories for promotional photos and promotional cues such as scarcity message, conformity message and credibility cues. Finally, we also identify the customer segments that share similar selection characteristics. Therefore, The following research questions were proposed:

RQ1: What are the factors and attributes displayed on a SERP that could enhance tourists' selection?

RQ2: What are the identified themes for gastronomy experiences images?

RQ3: What are the important levels of each proposed information cue through P2P online platform (i.e., Airbnb)?

RQ4: What are the latent market segments of tourists for gastronomy experiences based on displayed information cues? What are the differences or similarities in information filtering among different market segments?

In summary, this study first mined Airbnb gastronomy experiences data from the website. Based on the real website data, it determined the levels of each information cue. For identifying the information cues in the photos, object detection was performed using Google Cloud Vision API. It is a popular choice for identifying objects in the photos as the highly accurate pre-trained deep machine learning models are employed. Next, the survey was designed incorporating six identified information cues at different levels, and survey data were collected. Choice-based conjoint analysis was performed to understand the role of online information cues in decision-making process.

Our research has theoretical, methodological and practical contributions. Theoretically, it extends the application of signaling theory and heuristic systematic model in the gastronomy tourism domain to explain how tourists process online information. It successfully bridges the gap by introducing promotional photos and host credibility information cues in an experimental study. Methodologically, pre-trained machine learning models are employed to find cues in the online photos, which are the real-world images scraped from Airbnb. The result serves as a solid foundation for conjoint analysis survey design. In addition, the survey-based conjoint analysis further identified important information cues to each level and provided insights into each market segment. The findings provide substantial practical implications for marketers, web information displays, and tourists' online information filtering, processing, and selection.

2.Literature review

In this section, we first comprehensively review the literature on two-sided travel marketplace and expand on Heuristic-Systematic Model (HSM) in explaining consumer decision-making and preferences. Next, we provide an overview of the attributes displayed through Airbnb experiences search page and include the key theories such as Signaling Theory. In detail, based on the previous literature, we address the important role of images and each one of the attributes, and discuss how each one of them may influence the decisions of consumers.

2.1 P2P marketplace and information processing

2.1.1 P2P travel marketplace

A P2P travel marketplace is an E-Commerce platform where users can organize tours or activities and book as a guest (Filistrucchi et al., 2014). Meanwhile, the definition of the vendor has also been transformed because vendors are now regular consumers as well as merchants. The traditional vendors cannot deliver value, but they can offer a value proposition and promote value co-creation; instead, P2P travel marketplace vendors deliver value, create brand image, share responsibility, and set prices (Kumar & Reinartz, 2016; Liang et al., 2018). One of the most successful cases of a P2P travel marketplace in the hospitality industry is Airbnb. It offers wide and diverse services, including lodgings, tours, and other range of activities (Lladós-Masllorens et al., 2020). Among the diverse services offered, previous literature mostly investigates the lodging aspect, tours, and other ranges of activities that have been overlooked.

Airbnb experiences, a sector that is designated on local tours, activities, and experiences “led by locals,” add value and contribute to the P2P travel marketplace (Airbnb, 2021). This is the real innovation that digitalization and digital platforms enabled the expansion of the market economy. In addition, the success of P2P travel experience can be summarized in two value propositions:

- Experience value proposition: “led by locals”;
- Credibility proposition: easy access and the establishment of a trusted marketplace through community engagement (Oskam & Boswijk, 2016).

The desire for social interaction, taste of authenticity, and a showcase of the “collective lifestyle” is often seen as the main distinguisher behind the growth phenomenon (Gansky, 2010; Ikkala & Lampinen, 2015; Oskam & Boswijk, 2016). With the increasing user rate on online P2P travel marketplace, how information cues impact behavioral motives need to be investigated further. Nevertheless, with most of the literature focusing on investigating how host information impact booking intention (Su & Mattila, 2020; Ye et al., 2017), reviews and social media influence booking intention (Chen & Chang, 2018; Kamble et al., 2020), less is known on how displayed web information impact booking intention on Airbnb experiences. Therefore, the study aims to fill the gap and identify critical aspects of consumers' comprehension of information related to gastronomy experiences.

2.1.2 Online information processing and theoretical foundation

With the advancement of digital media and online community influence on travel experiences, it is evident that the online information cues directly influence consumer decision-making. Researchers in the past have attempted to answer how do consumers perceive and filter information cues to make decisions. Two most commonly used theories are Heuristic-Systematic

Model (HSM) and signaling theory. HSM is theorized to explain information processing by assuming that individuals obtain information mainly through two cognitive processes: the heuristic process and the system process (Chen et al., 1999). Both types of processing require obtaining information and making decisions based on prioritizing the information cues. The information cues that appear to be more important and catch people's attention easier, appear to have a higher impact on decision-making. Understanding these cues is a way to understand signals, where signaling theory suggests direct attention to the important aspects is a way to strategically make decisions for consumers (Bergh et al., 2014; Spence, 1978).

Previous studies have tested and verified the role of online information cues through HSM and suggested that group opinions and preferences play a major role in information processing. Information cues such as ratings, reviews, and other evaluations through the online community significantly influence individuals' decision making by shaping the opinion formation (Kaplan & Miller, 1987; Luo et al., 2013; Xiao et al., 2018; Zhang et al., 2014; Zhou et al., 2016). As Hlee et al. (2018) summarized in their study, the hospitality and tourism online platforms generally segment online information cues into three types: review-related cues, source-related cues, and context-related cues. Review related cues including visual, textual, and lexical, whereas source related cues are concerned with credibility, such as reputation, identity, expertise, authority suggesting the source credibility.

Our study focuses on impression motivation and attempts to employ signaling theory and HSM to explain the impact of information cues' on online P2P marketplace on consumer booking intention. It is worth mentioning that the online booking Search Engine Result Page (SERP) is the first search results page, and consumers make their first judgments and decide if they would like to learn more about the experiences. So, when exploring SERPs, identifying the key determinants will make the experience stand out.

2.2 Online information cues on SERP

2.2.1 Visual illustration and thumbnails in food image

Visual illustration has always been discussed to be more effective compared to text information (Moon & Kamakura, 2017). Although previous consumer related literature has obtained some understanding on decision making in different contexts (Lee & Gretzel, 2012; Liu et al., 2013), the research on the role of visual information cues on gastronomy tourism-related decisions is limited (Balomenou & Garrod, 2019). Among limited research, from a persuasive travel website design perspective, (Kim & Fesenmaier, 2008) proposed that visually appealing stimuli (e.g., photos) are the most important tool to increase the persuasiveness of destination websites. An experimental study later examined the influence of photos on individual imagery processing and consumers' attitudes. The findings indicated that only photos on the website significantly affect consumers' attitudes, which further influence communication effects (Lee & Gretzel, 2012). The results highlight the role of photos in shaping consumers' attitudes and enhancing imagery processing. In detail, photos exert a substantial effect on tourists' perception of destination image, and the online destination image has a prominent effect on destination marketing (Rodríguez-Molina et al., 2015). Therefore, we study the role image plays in decision-making process of gastronomy experiences.

Furthermore, food elements can result in shaping the destination (Lai et al., 2018). Food consumption has become one of the main motivations for tourism, and local gastronomy experiences influence tourists' intention to visit (Mak et al., 2017). In the case of gastronomy marketing, visual illustration is even proved to be the most effective because it triggers mental stimulation of consuming food (Paivio, 2013; Yim et al., 2020). Furthermore, with a particular emphasis on metrics such as local food attractiveness, gastronomy-related activities, and people's interests, which are deemed important in forming local brand and local destination image (Che, 2006; Lin et al., 2011; Tellström et al., 2006). Consequently, to captivate and promote gastronomy experiences, hosts use the dynamic set of photos with different themes aim to attract tourists. Therefore, although gastronomy experiences are food and beverage related, the visual illustration might include various aspects such as nature view, people gathering, indoor layout, and décor, to best represent the locality culture involved in the gastronomy experiences (Horng & Tsai, 2010).

Given that website visual illustration, especially photographs, are often used for marketing and promoting purposes, visual appealing becomes a goal for practitioners (Kim & Fesenmaier, 2008). Thus, there is a need for additional research in understanding information processing and decision making through travel website displays, especially in understanding destination image formation and the role of photographs (Rodríguez-Molina et al., 2015). Online P2P travel marketplace such as Airbnb, have photos displayed on SERPs. The photos on SERP named thumbnails are usually smaller in size and are the most representative snapshots of the business (Song et al., 2016). It has been discussed that thumbnails are becoming increasingly crucial in influencing the online searching experience (Yuan et al., 2019), and a homepage with a thumbnail is argued to be more effective in facilitating information processing when compared to the progressive and list-view designs (Yu & Kong, 2016). However, there is a lack of understanding on how consumers evaluate the thumbnails compare to other information cues in the context of online travel websites.

2.2.2 Promotional cues

Promotional cues are an important part of SERPs. For instance, through Airbnb experiences page, there are two types of promotional cues on Airbnb search results: “availability is rare” and “usually sells out.” These are two messages delivering two different signals. “Availability is rare” is a scarcity message deliver the signal of low availability of the service (Teubner & Graul, 2020). Previous literature suggests that scarcity message would enhance the willingness to purchase due to the fear of missing out (Brehm & Brehm, 2013). The interaction of high popularity and low availability, according to law of supply and demand, creates a sense of "hot product or service" among consumers (Stock & Balachander, 2005). On the other hand, “usually sells out” is a conformity message. which conveys the signal of a product or service's high popularity and demand (Lascu & Zinkhan, 1999). Because eCommerce provides information cues to evaluate products or services, conformity and scarcity messages are more effective marketing strategies in the eCommerce environment than in offline marketing (Mou & Shin, 2018). As a result, conformity and scarcity messages have been widely utilized to increase sales on online marketplaces (Fenko et al., 2017). In our study, we consider the conformity and scarcity messages as a part of our experiment design.

Furthermore, we also consider a reputation measure such as, hosts' credibility on online P2P travel marketplaces. Host profiles on online sharing marketplaces, such as Airbnb, provide identities of the hosts and disclosed information is perceived as relevant and of interest to the potential guests (Ert et al., 2016). The perceived trustworthiness of host profiles is studied extensively due to their significant role in predicting various factors. Ma et al. (2017) employed mixed methods and developed a categorization of host profile descriptions, showing that the longer self-descriptions are perceived as more trustworthy. In addition, host credibility perception is a significant predictor of host choice. It is also examined to be positively associated with booking intention (Broeder & Remers, 2018). Moreover, host profile characteristics have been assessed to affect the Airbnb price (Tong & Gunter, 2020a) since establishing online trust is the first step in initiating transactions (Xie & Mao, 2017). Barnes and Kirshner (2021) found that perceived host profile credibility and attractiveness positively associate with Airbnb price increase to almost 5%. Although host credibility perception is positively associated with booking intention (Broeder & Remers, 2018), other objective measures such as ratings and number of reviews also play an important role (Barnes & Kirshner, 2021).

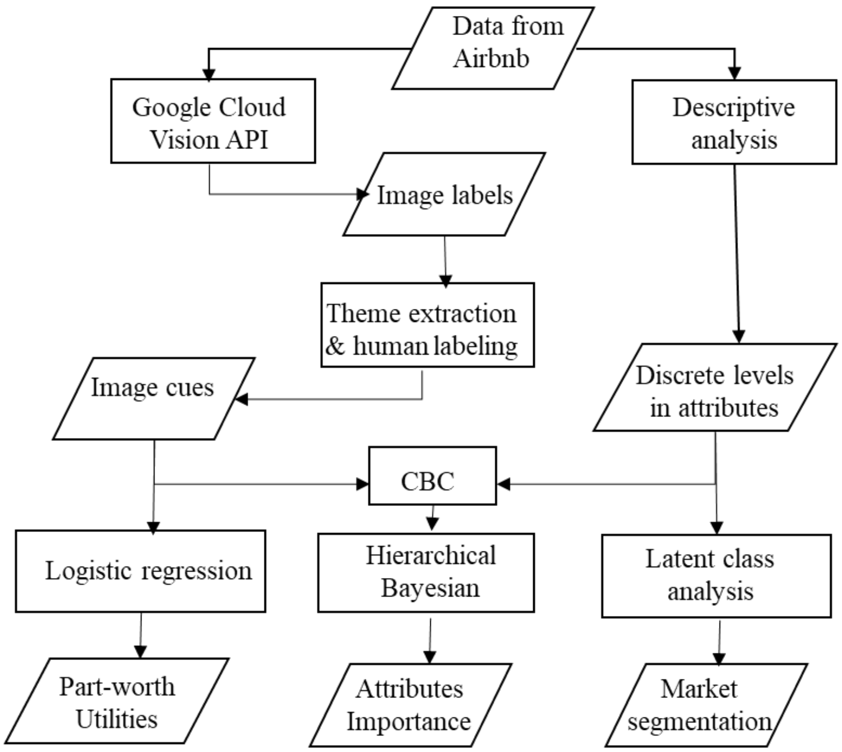
2.2.3 Price, rating, number of reviews

One of the unique aspects of the online tourism marketplace is that tourists have to purchase the product before the tourism experience, and the tourists' perception of value will be determined by the information online (Park & Kim, 2008). Generally, tourists instinctively associate value with price when gathering tourism product information. Thus, price information is always used as leverage to drive market share (Noone & McGuire, 2013). While the price significantly impacts tourists' value perceptions, non-price information is always integrated when making decisions (Kim & Park, 2017). Through the online travel marketplace SERP, in addition to price, information cues such as average ratings and numbers of reviews are normally available. They provide additional aspects for consumers to process information (Martin-Fuentes et al., 2020). Ratings often help consumers to filter the information and bring forth higher average rating products with more visibility (Nieto-Garcia et al., 2019). It serves as an important attribute to reduce the time and effort in the search. Additionally, ratings and the number of reviews complement each other. Specifically, average ratings provide an overall evaluation of the products, whereas the number of reviews validates the credibility of the ratings (Park & Kim, 2008). Therefore, both the information process and decision-making process often involve various online information cues (J. Kim et al., 2009; Liu & Park, 2015). In our study, we consider all three factors – price, rating and number of reviews.

3.Methods

This study's method contains two steps. In the first step, researchers scraped the data from Airbnb experiences website with all the gastronomy experiences based in the U.S. and performed text mining to decide on attributes' discrete levels. This provides a strong foundation for conjoint analysis design. Specifically, this study first reviewed the information displayed on SERPs of Airbnb experiences with a selection of food and drink category and closely examined the layout and attributes displayed through the SERPs page, including featured images. The second step contains a survey design aimed to simulate Airbnb experiences through the Airbnb app and ask participants to choose the ideal options. Further analyses were taken place to understand the online selection behavior, where the logit model was incorporated to calculate the part-worth utilities, Hierarchical Bayesian (HB) analysis to estimate the importance of attributes, and LCA to segment the market based on heterogeneity and homogeneity. Please see **figure 1** as the flowchart of the methods.

Figure 2-1 **Flowchart of methods overview**



3.1 Online data analysis

3.1.1 Text mining and image content analysis

Gastronomy experiences related data was collected in June 2021 from Airbnb experiences website by selecting the geographic location as the United States. In total, there were 585 experiences obtained. The dataset contains experience information such as name, ratings, number of reviews, price per person, activity duration, capacity, and all the image data, which covers the displayed information through Airbnb SERP. In total, there were 2,767 images collected. Unique identification numbers were used to make sure all the images were downloaded once.

Image data, as the unstructured data, is challenging to discover meanings behind the image (Lee, 2017). This study aimed to classify image data collected from Airbnb gastronomy experiences based on the images' overall themes. This step is to better serve the design of the conjoint analysis and have concrete support for image selections and overall themes. To accomplish this, the present study (1) extracted images in URL format through the selection of Airbnb gastronomy experiences; (2) using google vision Application Programming Interface (API), a pre-trained machine learning model, to assign labels to images; (3) based on the produced labels, the researchers manually coded the themes and generated image cues. The following section presents additional details of each step.

Recent advancement in computer vision provides tools to transform and interpret image data. Machine learning algorithms and pre-trained models in computer vision have been applied in tourism and hospitality literature, especially in adopting existing APIs, such as Yu and Egger (2021) and Arefieva et al. (2021) successfully adopted existing image APIs in clustering destination images. Similarly, the current study used Google cloud vision API to derive insights from gastronomy experiences images through Airbnb. 2,767 images were classified and assigned categorical labels using Google's pre-trained machine learning models. This approach aims to leverage existing AI tools to improve the efficiency of image cues extraction and provide validity for different image cues interpretation.

After applying Google Vision API, the researchers further categorized the images through identified labels and hand-coded images into six different cues: (1) food and drink, (2) group walking tours, (3) host demonstration, (4) indoor group activities, (5) layout and spacing, (6) outdoor nature view. This further benefits Airbnb hosts and Airbnb marketing specialists, and they would be interested in learning about what types of labels in each image cue often appear in attracting tourists. For example, labels such as "cuisine," "ingredient," "food," "dishware," "bottle," "drinkware," "table," "fruit" are closely associated with food and drink. Therefore, images identified with these labels were categorized as "food and drink." To provide an overview of the identified labels in each image cue, **figure 2** contains six-word clouds to help visualize the results. Each cloud selected the top 50 appearing labels in represented image cues. In addition, **Figure 3** demonstrates examples from each image cue. This section successfully answered research question 2.

Figure 2-2 **Image cues word clouds.**

Food and drink

Group walking tours

Host demonstration

Indoor group activities

Layout and spacing

Outdoor nature view

Figure 2-3 **Examples from each image cue.**

For validation and reliability checking, one researcher conducted two rounds of coding, with two weeks in between, and Cohen’s Kappa Values were calculated to verify inter-rater reliability (Zwick, 1988). In inter-rater reliability for two rounds of coding reached 0.89, suggesting almost perfect agreement between two rounds of coding. In addition, machine-human agreement on the Google Vision API produced labels were also verified through random selection of 100 images from each image cue, where one researcher closely compared the images with labels. In total, 600 images were compared with the labels produced from Google Vision API, and the agreement level reached 92%, which demonstrated the high fitness between images and produced labels.

3.1.2 descriptive results on gastronomy experiences and identified image classes

In total, 585 gastronomy experiences were included in the dataset, and the dataset included all the food and drink 1`activities located in the U.S. by June 2021. In total, attributes descriptive of star ratings, the number of reviews, time spend, capacity, and price are displayed in **Table 1**. All the attributes are numeric values; therefore, the table includes the quartile points of the data collected and the range. The quartile values are used to determine levels for conjoint analysis in the next step. In addition, the distribution of the image cues is displayed in **Table 2** and reports the number of images in each image cue.

Table 2-1 **Airbnb gastronomy experiences descriptive information (N = 585)**

Attributes	Quartile 1	Quartile 2	Quartile 3	Range (Min./Max.)
Star Ratings	4.8	4.9	5	4 to 5
Number of reviews	61	172	655	0 to 1201
Time spend	75	90	150	60 mins to 10 hours
Capacity	5	8	10	1 person to 20 people
Price	22	65	163	$2 to $780

***Table 2-2* Distribution of image cues.**

Image cues	Number	Percentage
food & drink	718	25.95%
group walking tours	642	23.20%
host demonstration	428	15.47%
indoor group activities	509	18.40%
Layout and spacing	256	9.25%
Outdoor nature view	214	7.73%
Total	2,767	100%

3.2 CBC Research design

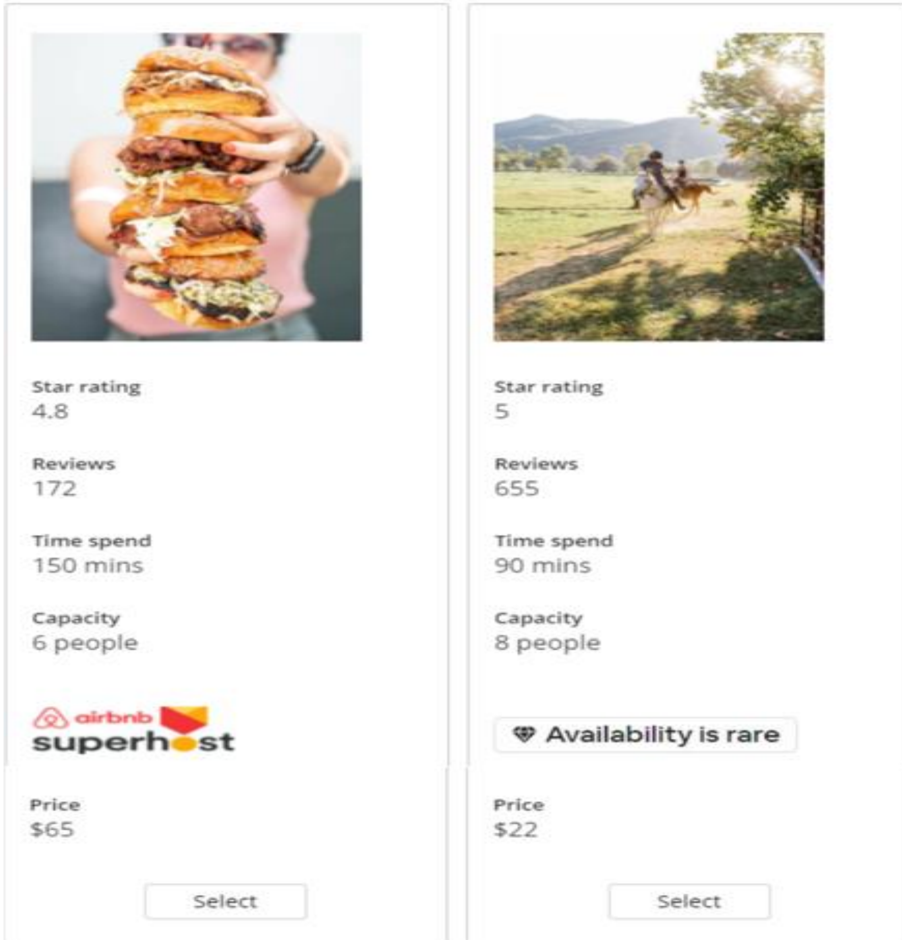
Based on the descriptive results, a self-reported online survey using the CBC experimental design was developed by Lighthouse Studio 9.13.1. CBC is a well-known marketing research technique that helps explain how each information cue of a product or service will affect the customer's decision-making process (Curry, 1996) It is also widely used to understand how business websites displayed information cues guide consumer decision-making (Arenoe & van der Rest, 2020). The number of research questions in the CBC should be between 8 to 20 in design, and each question should contain options for participants to choose from. In Meissner et al. (2016)'s study, it suggested that given two options for each question are the best approach due to the capacity of attention spend for experimental design.

In this study, we chose to display two options in each question and designed a survey to explore the information cues that influence participants' intention to participate in the Airbnb gastronomy experiences. In addition, the survey includes demographic questions and questions measuring the previous experiences, familiarity, and awareness of Airbnb platform. The experiment includes seven attributes: (1) featured images, (2) star ratings, (3) numbers of reviews, (4) time spend, (5) capacity, (6) price, and (7) promotional cues. Five attributes have numeric values and obtained quartile points from the online data among the seven attributes. Additionally, the featured image attribute obtained from the image analysis results in establishing feature image levels. Lastly, as for promotional cues, Airbnb experiences website contains two types of promotional cues: "availability is rare" and "Usually sells out." However, when searching for a place to stay, Airbnb displays "Superhost" on the home page as an additional promotional cue. "Superhost" not only demonstrates the great service quality but also signifies the credibility of the hosts and recognition from Airbnb (Gunter, 2018; Liang et al., 2017). As of now, Airbnb experiences page hasn't been included. Therefore, it would be compelling to incorporate the superhost badge into promotional cues and test Airbnb gastronomy experience booking intention. All the aforementioned attributes are displayed on the Airbnb platform. More details on attributes and levels in the CBC design are displayed in **Table 3**. All the above successfully addressed research question 1, where attributes and levels are identified. **Figure 4** provides an example from the respondent view of CBC survey.

Table 2-3 **Attributes and levels in the CBC analysis.**

Attributes	Levels	Attributes	Levels
Featured images	food & drink group walking tours host demonstration indoor group activities Layout and spacing Outdoor nature view	Time spend	75 mins 90 mins 150 mins
		Capacity	5 people 8 people 10 people
Star Rating	4.8 4.9 5	Promotional cues	Availability is rare Usually sells out Superhost Badge N/A
Number of reviews	61 172 655	Price	$22 $65 $163

Figure 2-4 **Respondents view of CBC survey.**



3.3 Sample and data collection for CBC

Since Lighthouse Studio 9.11 has the capacity to design and distribute the survey through online channels. Amazon Mechanical Turk (Mturk), a crowd-sourcing platform, was used for data collection. It is an efficient sampling method that are more inclusive with participants having a diverse background (Hauser et al., 2019). In response to the concerns on data validity, attention check questions were implemented in the survey to verify the consistency (Cobanoglu et al., 2021). The target population for this study was participants who live in the United States and were at least 18 years old. Invalid, incomplete, or inconsistent responses were discarded from the data analysis. In total, 391 valid responses were used for the data analysis.

3.4 Data analysis

The collected data was analyzed through Lighthouse 9.11 (Sawtooth Software). Logit regression was used to calculate part-worth utility. The part-worth utility is a measure of attribute importance at the featured level, and HB Analysis was conducted to estimate the importance of attributes (Gieseking, 2009). After that, Latent Classes Analysis (LCA) was used for marketing segmentation based on heterogeneity and homogeneity. The rest of the descriptive analysis used SPSS.

4. Results

4.1 Demographic profile

A total of 581 respondents completed the survey. Exclusion criteria included:

- Respondents failed to pass attention check questions.
- Inconsistent response in age and year of birth.
- Completing the survey within 6 minutes.

The average duration to complete the survey is 9 mins. After the data cleaning, a total of 391 useable responses were included in the final analysis, which satisfies the data sufficiency based on Peduzzi et al. (1996), which says that as for simulation study, the minimum sample size should be considering ***q*** the number of questions shown to each participant, ***a*** the number of alternatives provided per question, and ***c*** the maximum number of levels of any attribute.

$$n \geq \frac{1000c}{qa}$$

In this study, the simulation has eight questions shown to each participant, two alternatives provided per question, and the maximum number of levels is 6. In total, participants should be larger than 375, and 391 satisfy the requirement. Of the participants, 32.5% were female, and 67.3% were male. 68% of participants are millennials (between 26 to 41), who contribute to the majority of food and drink consumers in the U.S. In addition, 86.2% were white in ethnicity, and

90.8% of participants held at least a four-year college degree. As far as the Airbnb platform, the majority of the participants (45.5%) indicated that they are very familiar with Airbnb, with 15.9% indicated that they are extremely familiar with the Airbnb service. In terms of awareness of Airbnb experiences, 42.2% of the participants indicated that they have a high awareness of Airbnb experiences. Please see **table 4** for details.

Table 2-4 **Demographic information**

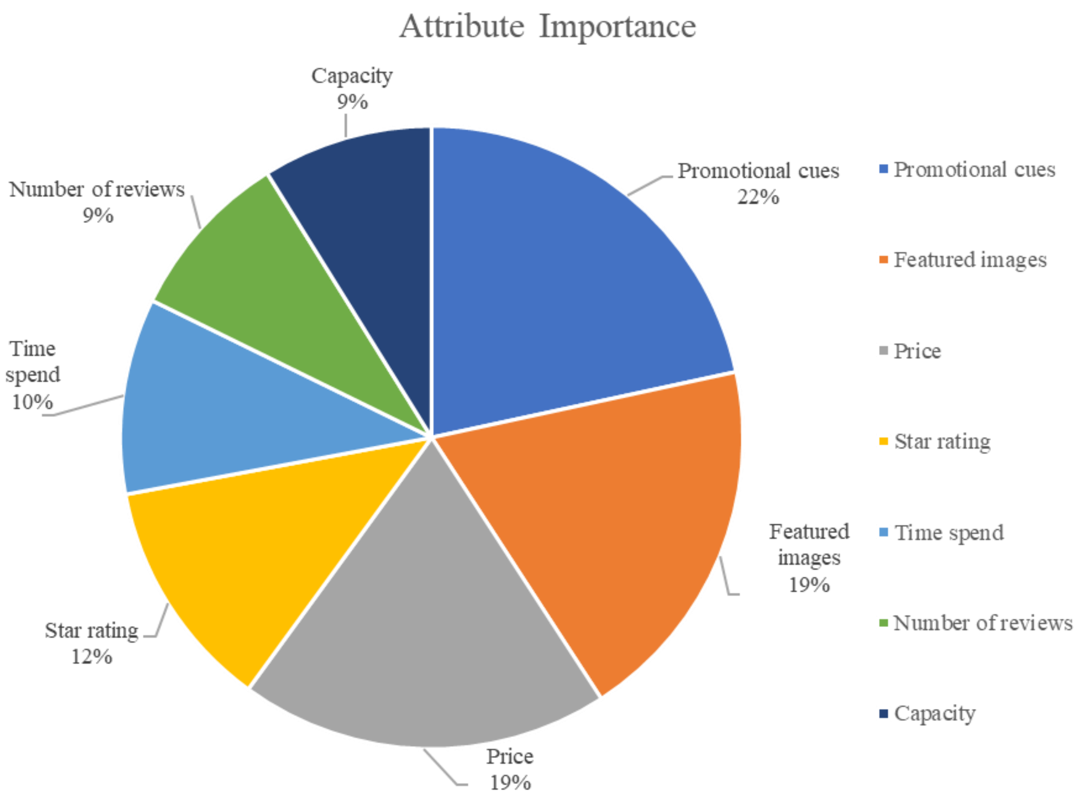
	Frequency	%
Gender		
Male	263	67.3
Female	127	32.5
Prefer not to say	1	.3
Ethnicity		
American Indian or Alaskan native	11	2.8
Black or African	12	3.1
Hispanic/Latino	11	2.8
Native Hawaiian or Pacific Islander	1	.3
White or Caucasian	337	86.2
Asian	17	4.3
Prefer not to say	1	.3
Highest education	0	0
Less than high school	0	0
High school graduate	8	2
Some college	16	4.1
2 year degree	12	3.1
4 year degree	242	61.9
Master degree	110	28.1
Doctorate	3	.8
Annual household income		
Less than 20,000	27	6.9
20,000 to 39,999	95	24.3
40,000 to 59,999	154	39.4
60,000 to 79,999	61	15.6
80,000 to 99,999	33	8.4
100,000 and above	21	5.4

4.2 Attribute importance and part-worth utilities

A Logit Model was used to examine the influence of attributes' composition on consumer behaviors. The model fit was accepted $\chi 2$ (24, N = 391) = 181.78, p <0.01). The value for Chi-Square is 181.78, which is well above the minimum requirement of 37.6 ($p < 0.05$) at 24 degrees of freedom so that the composition of attributes' significance can be assumed. The Root-Log-Likelihood (RLH) value range between 0.2 to 1, where 1 means perfect fit. As far as the conjoint survey design, respondents were asked to choose from two alternatives with eight displayed questions. In our model result, the RLH value is 0.51, indicating the reasonable suitability of the empirical data (Gieseking, 2009). In addition, the t ratio was calculated to evaluate the significant levels within the attributes.

Based on the HB (algorithm, the importance of the attributes and part-worth utilities were calculated. The importance of attributes indicates the relative importance of each attribute during the selection process. The individual response from each respondent is evaluated to measure the overall attributes' importance (Orme, 2006). **Figure 5** demonstrated the outcome of attribute importance, promotional cues (22%) have the highest importance level, the next highest attributes are featured image (19%) and price (19%), followed by star rating (12%), and time spend (10%). The lowest two attributes of importance are the number of reviews (9%) and capacity (9%).

Figure 2-5 **Average attribute importance.**



The part-worth utilities (i.e., preference scores) further present the relative preferences of individual levels in each attribute (**Table 5**). The t ratio was calculated to evaluate whether the effect of a specific level is significantly different from the mean of zero for all levels within the attributes (Rao, 2014). From the results, it is clear that, in general, respondents prefer higher ratings, a larger number of reviews, less time spend, medium crowd requirement, and lower prices. As for featured images, participants particularly prefer indoor group activities and the food and drink category. Most importantly, promotional cues as the highest attribute importance, Superhost badge level is significantly superior to the other three levels. Therefore, research questions 3 is answered.

Table 2-5 **Significance and Part-worth (Zero-Centered Diffs) (N =391)**

Label	Average Utilities (Zero-Centered Diffs)
featured images	
Food and drink	8.39
Group walking tours*	-11.16
Host demonstration	-13.46
Indoor group activities**	27.96
Layout and spacing	0.84
Outdoor nature view*	-12.57
Star rating	
4.8**	-19.86
4.9	-1.16
5**	21.02
Number of reviews	
61	-6.24
172	-3.81
655*	10.05
Time spend	
75 mins	2.97
90 mins	9.28
150 mins	-12.24
Capacity	
5 people	-7.80
8 people	9.02
10 people	-1.22
Promotional cues	
Availability is rare**	-19.98
Usually sells out**	-40.44
Superhost badge**	61.40
Blank	-0.98
Price	
$22**	28.78
$65*	9.30
$163*	-38.09

*Note: * p <.05, ** p< .01.*

4.3 Latent Class Analysis (LCA)

LCA was further used to identify the unobserved subgroups among participants with a selected set of indicators and identify the presence of preferences heterogeneity (Nylund-Gibson & Choi, 2018). The LCA result suggested an acceptable model fit based on the number of segments ranging from two to five, and the increasing number of segments led to the log-likelihood growth; it is not suitable to determine the number of segments. Therefore, CAIC (Consistent Akaike Information Criterion) and BIC (Bayesian Information Criterion) were considered to select the most appreciated group segments. Both CAIC and BIC value provides clear separation among segments in terms of the value. Among the two to five segments, the two-segments solution was shown as the best due to the lowest CAIC (5413.32) and BIC (5476.32) value, which indicates a better balance between fit and complexity (Bruwer & Li, 2017; Software, 2019). Based on the goodness-fit-criteria, two segments were the most ideal group segment: group 1 (13.8%, *n* = 54), group 2 (86.2%, *n* = 357). Please see **table 6** for details.

Table 2-6 **Goodness-of-fit criteria of the LCA.**

Segments		**Log-likelihood**	**CAIC**	**BIC**	**Chi-Square**	**Relative Chi-Square**
2		-2535.19	5413.32	5376.32	336.17	9.09
3		-2498.57	5516.19	5460.19	409.40	7.31
4		-2460.05	5615.25	5540.25	486.45	6.49
5		-2400.90	5673.05	5579.05	604.76	6.43

Similarly, to understand the different preferences within two groups, the attribute importance of the two-segments solution was demonstrated (**Table 7**). From the results, the most important attribute in group 1 is price, whereas the most important attribute in group 2 is promotional cues. Both groups value featured images and star ratings. As far as the lowest attribute importance, for group 1 is time spend and for group 2 is the number of reviews. Apparently, the two groups have distinctive preferences and emphases during the selection process. Subsequently, for a more comprehensive look, part-worth utilities were again performed based on a two-segments solution. Table 7 displays the importance of attributes for two-segment solution.

Table 2-7 **The importance of attributes for two-segment solution**

Attribute Importance	**Segment 1 (%)**	**Segment 2 (%)**
featured images	9.27	19.44
Star rating	11.70	18.35
Number of reviews	7.53	3.75
Time spend	1.44	6.25
Capacity	5.85	4.74
Promotional cues	4.95	43.53
Price	59.27	3.94

Derived from part-worth utilities in a two-segment solution, under featured images, group 1 has a similar level of preferences on three levels: host demonstration, indoor group activities, layout, and spacing. These help to visually understand the surroundings. As for group 2, the most preferred level is indoor group activities, which indicates they prefer to see the crowd to understand the activity. As far as star rating and review numbers, both groups prefer higher ratings and a higher number of reviews. Similarly, two groups' preferences are consistent and aligned with time spend estimation and capacity. The differences are more distinctive in levels of promotional cues and price. As for promotional cues, group 1 has a negative attitude toward promotional cues; respondents would rather choose activities with no signifying effect, whereas group 2 has a strong preference for the Superhost badge, but not other promotional cues. As far as price, although group 1 and 2 both prefer a lower price, from the result, it seems that group 1 have a strong preference for a lower price, whereas group 2 seems to have a higher tolerance in terms of price range because in price attribute, the most preferred level for group 2 is at $65. **Table 8** contains detailed information on part-worth utilities for two segments.

Table 2-8 **Part-worth utilities for the segments.**

Attributes and levels	**Rescaled Utilities (Zero-Centered Differences)**		
featured images	**Group 1**	**Group 2**	**Total**
Food and drink	-9.76	28.53	8.39
Group walking tours	-44.67	-52.22	-11.16
Host demonstration	20.25	-26.10	-13.46
Indoor group activities	15.65	83.83	27.96
Layout and spacing	15.42	6.71	0.84
Outdoor nature view	3.10	-40.75	-12.57
Star rating			
4.8	-17.10	-64.03	-19.86
4.9	-32.38	-0.38	-1.16
5	49.48	64.40	21.02
Number of reviews			
61	-33.80	-8.35	-6.24
172	18.90	-8.97	-3.81
655	14.90	17.31	10.05
Time spend			
75 mins	-1.20	-0.22	2.97
90 mins	5.64	21.98	9.28
150 mins	-4.44	-21.76	-12.24
Capacity			
5 people	-18.51	-16.01	-7.80
8 people	22.43	17.16	9.02
10 people	-3.92	-1.15	-1.22
Promotional cues			
Availability is rare	-4.30	-70.94	-19.98
Usually sells out	-14.19	-108.19	-40.44
Superhost badge	-1.95	196.55	61.40
Blank	20.44	-17.42	-0.98
Price			
$22	187.60	-0.02	28.78
$65	39.67	13.80	9.30
$163	-227.27	-13.78	-38.09

To further investigate the causes of the differences, the independent sample t-test was used to analyze whether participants in the segment suggested by LCA showed differences in gastronomy activity involvement, Airbnb platform searching and booking frequency, and Airbnb experiences awareness and familiarity. Questions on involvement and booking frequency were adopted from Cho (2009). From the t-test result, it turns out that Airbnb searching and booking frequency and awareness of Airbnb experience are significantly different in the two groups. **Table 9** demonstrated the questions with significant results. From the results, group 1 respondents have less experience with the Airbnb platform since they search less frequently and book less frequently through the Airbnb platform. In addition, they are less aware of Airbnb experiences compared to Group 2. Therefore, group 1 respondents are labeled as "inexperienced Airbnb users," and group 2 respondents are labeled as "experienced Airbnb users."

Table 2-9 **Independent sample t-test results.**

Questions	Group 1	Group 2	t
How often do you use Airbnb to search for travel information?	2.67	3.23	-3.03***
How often do you book through Airbnb?	3.01	3.32	-2.17*
Are you aware of Airbnb experiences (e.g. local tours, local workshop?	2.68	3.28	-3.55***

Note: ** $p < .05$, ** $p < .01$, *** $p < .001$. Measured using the five-point Likert-type scale, ranging from 1 (hardly ever/strongly disagree) to 5 (always/strongly agree)*

By comparing the demographic background between group 1 and group 2, group 1 has slightly fewer males (58.5%) compared to group 2 (68.8%). As far as age groups, group 2 contains more Gen-Z and millennials population, whereas group 1 has a higher percentage of participants older than 46. Educational wise, group 2 has a slightly higher percentage on the educational level under bachelor's degree whereas group 1 has a higher percentage with people with bachelor's degree or higher. In terms of income level, group 2 has a higher percentage of income above 80,000, whereas group 1 has a higher percentage of income below 59,999. This might also explain group 1 is more sensitive and have stronger preferences for a lower price. Based on the results above, research question 4 is fully answered.

The demographic information on individual segments is shown in **table 10.**

Table 2-10 **Demographics of the two-segments respondents**

	Group 1 Frequency (%)	**Group 2** Frequency (%)
Gender		
Male	58.5	68.8
Female	39.6	31.2
Prefer not to respond	1.9	0
Age		
18–25	3.8	9.5
26–35	35.8	57.7
36-45	37.7	18.9
46-55	15.1	8.6
≥56	7.6	5.3
Education		
High school or less	0	3.3
High school graduate	5.7	2.7
Some college	0	3.3
Associate degree	0	0.3
Bachelor's degree	83	86.7
Graduate degree	9.4	3.6
Prefer not to respond	1.9	0.3
Household income		
Less than $20,000	0	0
$20,000-$39,999	3.8	1.8
$40,000-$59,999	11.3	3.0
$60,000-$79,999	5.7	2.7
$80,000-$99,999	58.5	62.4
$100,000 and above	17	29.9
Prefer not to respond	3.8	0.3

5. Discussion and conclusion

Essentially, this study has two sets of findings. The first relates to the importance of promotional cues in Airbnb gastronomy experiences, especially the Superhost badge. For instance, we find evidence that potential tourists prefer to have some validation on host credibility, as Superhost badge is the most preferred level, and promotional cues are the most important attribute. This is especially not surprising as the Airbnb platform is a peer-to-peer platform, and Superhost status provides validation on host service quality, experiences, and ratings (Ert & Fleischer, 2019; Gunter, 2018). In addition, from the findings of Liang et al. (2017) and Teubner et al. (2017)'s studies, Superhost badge is more likely to receive reviews, and people are willing to pay more for accommodations with the Superhost badge. However, through Airbnb experiences SERPs, it is not included. In our study, Superhost badge's signaling effect is empirically verified in Airbnb experiences setting, and its impact on gastronomy experiences booking intention is manifest. In addition to promotional cues, featured image and price have all proven to be excessively relevant to Airbnb gastronomy experiences selection. Images again demonstrated the ability to attract demand. On top of that, from the featured image utility scores, preferences on image themes further provide insights and guidance to Airbnb hosts on how to enhance their attractiveness through SERP on Airbnb. It turns out people prefer to see indoor group activities, food and drink categories, and layout spacing. With gastronomy-related experiences, people are naturally more curious about the surroundings and intrigued by the food and drink-related image. Similarly, Oliveira and Casais (2018) found that when making a restaurant selection online, it appears more important for people to view the food and physical space of the restaurants from user-generated photos. As far as the most preferred level, "indoor group activities," people can easily connect with the images because they'd like to picture themselves in the same settings. Due to the nature of the peer-to-peer platform, the experiences are also considered as value co-creation (Casais et al., 2020). Therefore, group indoor activities images satisfy the curiosity of the surroundings and show the interaction among hosts and tourists to reproduce the co-creation process and display a certain level of authenticity. This aligns with previous studies' findings that one of the greatest advantages of Airbnb platform is its service originality and authenticity (Akarsu et al., 2020;

Birinci et al., 2018; Casais et al., 2020). To summarize, these image themes provide a more rigorous explanation of the tourism selection process with the evidence of empirical findings.

Another set of findings focuses on market segments. From Latent class analysis results, a two-segments solution was adopted. Based on respondents' selection, they've been categorized into two groups. The preferences of these two groups are distinctively different from one another. The first group is labeled "inexperienced Airbnb users," and group 2 is labeled "experienced Airbnb users." The rationale under two groups labels is the results from the independent t-test, where there is a statistical significance on Airbnb platform searching and booking frequency, Airbnb experiences awareness. Inexperienced Airbnb users (group 1) have a much lower booking and searching frequency and are not too aware of Airbnb experiences. They are more price-sensitive and care more about ratings. In contrast, they are less drawn to the images compared to group 2. As far as the rest of the attributes, the attributes' importance are all at a similar level. From the demographic background, inexperienced Airbnb users tend to have more respondents over age 55 and a higher proportion of household income less than 59,999. Being price sensitive can be the unfamiliarity of the Airbnb services, and they tend to use ratings and price as the familiar signals to make selections. Experienced Airbnb users are more aware of the Airbnb platform and service provided. Therefore, they are more likely to use familiar signals that appear in accommodation services: "Superhost badge" to make selections. Next, they would rely on the visual elements and evaluate ratings, time spend, capacity, price, and the number of reviews that make the selection. Interestingly, the least favorable image theme for both groups is a group walking tours. This provides additional insights on what to avoid in marketing gastronomy experiences through Airbnb.

6. Implications

6.1 Theoretical implications

Overall, the study contributes to the literature in three ways. First, it contributes to the tourism and hospitality literature by considering a critical research topic in a popular and emerging service sector: P2P local gastronomy experiences. This topic is to understand how potential tourists evaluate and process P2P online tourism information. As we have discussed in the literature review, information cues listed through the online platform can directly affect booking intention and for people to process information. Tourism marketing and consumer behavior are among the many academic fields that are interested in related topics (Casais et al., 2020; Dolnicar, 2019; Liang et al., 2017). The study uses a unique tourism sector, gastronomy tourism, and empirically tested the importance of information cues through a holistic approach. Selecting gastronomy experiences as one of the major categories of Airbnb experiences is beneficial in narrowing down the scope and providing a more detailed, tailored solution. Conjoint survey design fully considered all the elements that appeared through Airbnb experiences SERP, a simulation including featured images, which is a great advantage to test the important roles from full aspects through online information cues, with the consideration of image attribute.

Second, the study identified image cues from existing image data on Airbnb gastronomy experiences. The image object detection algorithm provided a novel and effective way of understanding the images. This study took advantage of a pre-trained image recognition model to gain insights from each identified image cue. Human labeling was incorporated for validation purposes. More importantly, all the attributes and levels are set based on the existing online data, which provides robust support for CBC study design. As we have noted from the exploratory results, certain types of signals appear to be more important and preferable. The findings confirmed the importance of signaling effect, visual image roles, and each information cue's weight on gastronomy tourism booking intention. It has implications for the literature on CBC designs, and the methods are replicable. CBC is a common practice in understanding preferences and is applied by many tourism marketing and consumer literature (Hung et al., 2019; Meyerding et al., 2019; Zhang et al., 2021). However, limited studies were able to incorporate visual elements. It is evident that the role food and drink photos play in the case of gastronomy marketing. It is proven to be a more effective approach because it evokes mental stimulation of food consumption (Paivio, 2013; Yim et al., 2020). For this study, the mix-method approach, which allows the study design to incorporate visual elements and construct a robust study design based on online data, is one of the main contributions.

Third, the uniqueness of P2P platform led to the discussion of evaluating quality of the service from trust and credibility towards the hosts. Previous literature revolving Superhost badge argued that with Superhost title, it has a strong effect on the economy benefits, perceived value, review numbers and even odds of being booked (Ert & Fleischer, 2019; Gunter, 2018; Liang et al., 2017; Yao et al., 2019). However, the booking intention on Airbnb experiences have never been empirical tested with a consideration of all online attributes. In addition, this further contributes to promotional cues that displayed through P2P platform. In this study, it turns out popularity cue “it usually sells out”, and scarcity cue “the availability is rare” displayed through Airbnb experiences are two unpopular options compare to host credibility cue “Superhost badge.” This is due to the nature of P2P platform; the influence of hosts’ credibility cues surpasses both traditional scarcity cues and popularity cues. The results from this study further enhanced the concept of trust and credibility, and the role its playing in consumer selection on P2P platform.

6.2 Practical implications

Practical implications for the current study are twofold. First, it provides directions for hosts to stand out from the crowd and tips to avoid ineffective marketing. Ratings and the number of reviews are external indicators that hosts don't have entire control over. The best a host can do is tailor the marketing information cues such as images, modify the experiences to cater to the target audience, and make sure that tourists feel the price listed is worth the experience during the selection process. Hosts can start by improving online appeal by displaying the image themes that are more preferred by the audience. From the LCA results, inexperienced Airbnb users and experienced Airbnb users have different preferences regarding the attributes and levels. From the aspect of the featured image, both groups prefer to learn about their surroundings more and picture themselves in the activities. They want to have a sense of what they are paying for as intangible and tangible services. Therefore, they prefer to see images of indoor group activities so they will have a sense of interaction among the tour groups and hosts. Inexperienced Airbnb users also enjoy seeing host demonstrations and experienced Airbnb users prefer appearing in food and drink photos. Layout and spacing also provide ambiance and atmosphere for tourists to evaluate the activities surroundings better. As far as less preferred themes, Airbnb food and drink experiences contain a great amount of group walking tours (23.2%), taking the second place. In reality, neither group prefers "group walking tours" images. Therefore, hosts should avoid displaying images in this category.

Second, it provides suggestions for Airbnb platform. Airbnb experiences as a relatively newer service sector, is experiencing a quick developing phase. The empirical results from the CBC study indicate that promotional cues are critical, and Superhost badge can lead to a higher booking tendency. Incorporating Superhost badge can benefit both Airbnb platform and the host. First, Superhost badge is a well-recognized signal to experienced Airbnb users, and it has a well-established filtering criterion internally through Airbnb accommodation service sector. Similar criteria can be set for Airbnb experiences hosts. This is also a good way to encourage more hosts to promote their services through Airbnb and trigger the intrinsic motivation of existing hosts using the gamification concept. Previously this has been verified in the literature that the badge system works very well to engage and motivate service providers (Gunter, 2018; Liang et al., 2017). Considering the weight of Superhost badge, and its signaling effect in booking, hosts will be more likely to strive for this goal and be more willing to show loyalty to Airbnb platform.

7. Limitations and future research

This study has serval limitations. First, the study scope is limited to gastronomy experiences. It indeed has some implications for Airbnb experiences in general; however, the findings have a better explanation power within gastronomy experiences. Second, due to the online data collection date (June 2021), there might be an increasing number of Airbnb experiences under the food and drink category. The online data included in this study did not consider any changes made and the added experiences after June 2021. As for future research, more data types can be considered and included in the analysis. Other online platforms can be included to expand the scope of the study and compare among different platforms. Third, the results of the present study did not reveal mitigation effects among online information cues. An example would be potential tourists who might have a higher price tolerance if the experience has a Superhost badge or 5-star ratings as an indication of perceived high service quality. Future research might design research using other methods to further investigate the mitigation effect among the displayed information cues.

Chapter 3 Exploring post-experience evaluation of gastronomy tourism experiences through Airbnb

1.Introduction

Gastronomy experiences have become the anticipated offering in destinations and attract abundant attention in academia (de Albuquerque Meneguel et al., 2019; Kim et al., 2019; Okumus & Cetin, 2018). 68% of tours and activities market are dedicated to food and drink, and from 4,000 travelers survey, 27% of travelers had done some type of gastronomy tours, classes, or experiences beyond just dining out (Ting, 2019). Fulfilling sensory needs lead to a higher evaluation of destination image, and gastronomy experiences have become an important element of diversification, regional brand establishment, and local culture identity (Mak et al., 2017; Mason & Paggiaro, 2012). Allocating resources to build gastronomy experiences and shaping promotional campaigns around food and beverage products has contributed to social and economic integration (Knollenberg et al., 2020). To foster the development of cultural and creative sectors internationally, the World Tourism Organization generates reports on worldwide gastronomy tourism since 2012 and has identified gastronomy tourism as one of the most creative parts of the tourism sector and contributes to job creation, entrepreneurship as a means to contribute to the sustainability development (UNWTO, 2021). It was no surprise that Airbnb debuted a collection named Airbnb experiences, and dedicated a category "food and drink," to specifically target gastronomy experiences (Ting, 2019).

Airbnb, as a form of online peer-to-peer (P2P) marketplaces, highly promotes entrepreneurship. Moreover, the market-based sharing economy has been widely recognized in the current stage of our society (Alrawadieh & Alrawadieh, 2018). With the majority of the literature focusing on Airbnb accommodation services (Lazard et al., 2018; Liang et al., 2019; Liang et al., 2020), little attention was spent on local experiences. “Food and drink” is one of the main local experience categories listed on the Airbnb website reflecting gastronomy tourism. Engagement in these experiences involves a comprehensive decision-making process. Nevertheless, information published on the website plays an effective role in attracting tourists (Mahrous & Hassan, 2017). With the emergence of information and communication technologies, tourists rely on dynamic information, such as visual illustration, ratings, online reviews, and price. Websites such as Airbnb provides a platform to display the advantages and distinguish the experiences (Ert et al., 2016; Lazard et al., 2018; Liang et al., 2019; Wu et al., 2021). As of now, Airbnb hosts can innovate in designing experiences that go beyond typical tourism, with more integration of local culture, local branding, more personalized and tailored experience to best satisfy tourists authenticity seeking (Airbnb, 2021). In addition, they have the ability to modify information through Airbnb experiences page. To stay competitive, the listings need to effectively catch people’s interests and make decisions on whether to participate (Swani et al., 2017).

Given that the important role sharing economy concept plays in the current stage, little is known on what affects post-experience evaluation in tourism gastronomy experiences. Therefore, there are many ambiguities and insufficient understanding of the effectiveness of online information and what influences post-experience evaluation. Accordingly, three research questions were proposed:

RQ1: What are some major themes tourists post on reviews reflecting the gastronomy experiences?

RQ2: What role does attribute related to visual information play in post-experience evaluation?

RQ3: What are the factors that influence tourists’ ratings through Airbnb food and drink experiences?

Hence, the current research took the U.S. as the country of interest, which has distinctive characteristics in many regions, and collected data on gastronomy experiences through Airbnb. This research has two main objectives. First, it investigates the tourists' reviews through Airbnb and explores the meanings and patterns behind the reviews to understand post-experience evaluation. Second, it aims to discover what information is displayed, and how they influence satisfaction. Section 2 comprehensively discusses the related literature, with a focus on gastronomy experience and website marketing. Then followed by section 3, with methods breaking down into two steps. The fourth part provides the results from the model implementation and discusses the results. The fifth part provides discussions based on the results. Finally, the importance of management, limitations, and suggestions for future research are discussed.

2.Literature review

2.1 Gastronomy tourism experiences

In the earlier literature, gastronomy tourism is always associated with culture and heritage tourism, which is why it's believed that the relationship between them is mutually parasitic, and gastronomy is a central part of the culture (Van Westering, 1999). Afterward, the awareness of the food importance in tourism has been steadily growing, and food started to embrace a range of gastronomic opportunities for tourists and broaden the destination's appeal (Hall et al., 2004). Thus, food and beverage are significant components of contemporary lifestyle and have become an emerging theme for tourism development (Smith & Xiao, 2008). The attractions on food and beverage promote local economic, and shape destination brand, as well as culture (Lai et al., 2018). It provides opportunities to diversify tourism by involving different professional sectors, such as chefs and producers, to co-create authentic experiences and to build diversity, multi-ethnicity awareness within tourism communities (de Albuquerque Meneguel et al., 2019).

Within the tourism discipline, literature discussing food often utilizing terms, such as "food and wine tourism," "tasting tourism," "gourmet tourism, " "culinary tourism," and "gastronomy tourism." Some of these terms are used interchangeably in the literature (Ellis et al., 2018; Horng & Tsai, 2012; Sánchez-Cañizares & López-Guzmán, 2012). "Gastronomy tourism," according to (Hegarty & O'mahony, 1999), is visiting the place of food within the culture. Similarly, Ellis et al. (2018) suggested that the term "gastronomy tourism" is host culture-centric and concerns the place of food and lifestyle of the society. Hence, the definition of "gastronomy tourism" is more inclusive with consideration of cultural influences on the culinary sector, including food and beverage appreciation. Therefore, this study adopts the term "gastronomy tourism" as its representation of cultural practice and sensory experiential heritage (de Albuquerque Meneguel et al., 2019).

The growing interest in traveling for food has been considered as one of the primary tourists' motivations and a significant consideration in destination selections (Hall et al., 2004; Henderson, 2009). Due to its close association with the local economy and cultural traditions of a place, the sense of authenticity and localization brings a substantial destination branding potential (Andersson et al., 2017). Activities associated with gastronomy experiences are expected to contribute to destination marketing, destination development and benefit a multitude of stakeholders (Du Rand & Heath, 2006; Roy et al., 2017). In addition, as gastronomy tourism gains popularity, destinations are in competition with many high-profile food places (e.g., Italy) (Montanari, 2009). As a result, these increased interests and competitions motivate tourism destination organizers, such as Airbnb hosts, to develop their marketing strategies (Kim et al., 2019).

2.2 Web marketing in gastronomy tourism

The thriving online tourism market has given destination organizers a powerful tool in destination publicity and has been considered as the most effective marketing channel (MacKay & Smith, 2006; Mahrous & Hassan, 2017). The information published online is greatly influencing tourists' pre and post-travel behaviors (Okumus & Cetin, 2018). Online tourism platform has many advantages on features such as cost-saving, transparency, accessibility, convenience, interactive communication on the interface (Y. H. Kim et al., 2009). Given this, marketers, destination organizers, and destination marketing organizations utilize both visual and textual content on websites (Dieck et al., 2018). In gastronomy tourism, both textual content and image content are critical in promoting gastronomy experiences and gaining a destination's success (Y. H. Kim et al., 2009). Due to the nature of gastronomy experiences being a mixture of tangible and intangible products, it is difficult to access the quality of the experience prior to engaging. Therefore, some of the factors are often considered by tourists before purchasing, such as online reviews, price, visual elements, etc.

As for online peer-to-peer (P2P) marketplaces, they have some distinguishment compared to traditional third-party booking websites. The marketplace platform itself is a venue to achieve individual service exchange where service providers have the freedom to publish content that is relevant to the service and can directly communicate with service receivers (Guttentag, 2015; Pizam, 2014). P2P marketplaces such as Airbnb, are a great example of sharing economy flourishing within tourism sectors. Prior studies have noted that the credibility and trustworthiness can be influenced by hosts' personal information, such as photos (Ert et al., 2016). Since trading with individuals involves higher risks than trading with a credible party (travel agencies, hotels), facilitating and evaluating products (experiences) can be more complex. Through Airbnb experiences, the added credibility, and a sense of personal human contact, the host information is displayed on the website to foster the sense of personal encounter (Ert et al., 2016; Tussyadiah & Pesonen, 2016). Host photos are often used for host identity verification and establishing trust (Guttentag, 2015). This further increases the complexity of tourists' decision-making process. Therefore, exploring tourism engagement requires a holistic evaluation of the website information.

2.3 The role of visual illustration in gastronomy tourism

As a complement to verbal descriptions, visual illustrations are commonly used in demonstrating and introducing food-related products (Septianto et al., 2019). It provides stimulation of the experiences and can provoke the viewers' imagination to better convey the favorable information (De Vries et al., 2012; Kim et al., 2019). Among different visual illustrations, photos are widely used in the hospitality and tourism sectors, especially in restaurants (Wu et al., 2021). The mental simulation of consumer experience promotes the effectiveness of visual illustration in food-related marketing (Paivio, 2013; Yim et al., 2020). For example, when encountering a visual illustration of a hamburger, it can effectively activate the sensory characteristics of hamburgers, such as taste and texture. This produces a more vivid mental simulation of the consumer experience and leads to a more positive image of products (Kim et al., 2019).

Other than the role of mental stimulation, the formation of the positive image from visual illustration requires credible and high-quality content. If the visual content used is controversial, outdated, or incorrect, it can easily trigger negative image formation and reduce credibility (Reino & Hay, 2011). Consequently, although visual illustration plays an important role in promoting gastronomy experiences, presenting effective content is critical for market success. In sum, to enhance the destination image and formulate a close link between the real gastronomy experience and its online information, visual illustration's role needs to be carefully examined. In addition, visual information in general, significantly affects consumers' image formation and communicate expectations (Lee & Gretzel, 2012). Therefore, in this study, researchers explored visual elements' characteristics effect and incorporated colorfulness attributes to see if they have an effect on post-experience evaluation.

2.4 Expectation disconfirmation theory

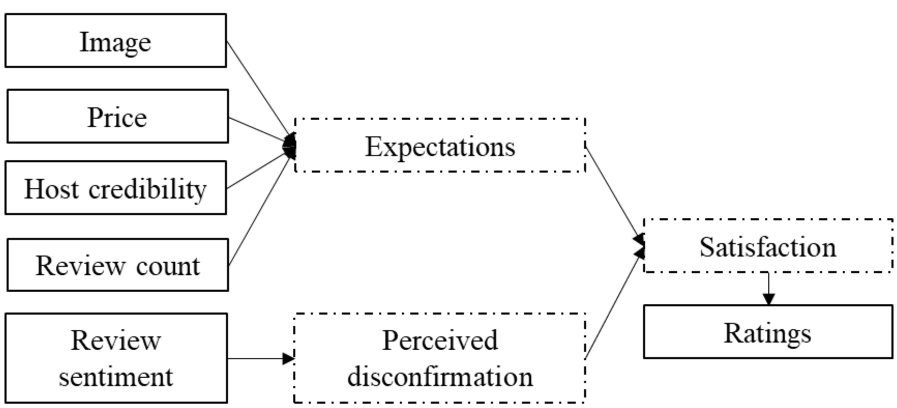
This study adopted Expectation Disconfirmation Theory as a theoretical framework and proposed that gastronomy tourists' satisfaction is determined by the match or mismatch between their expectations and the gastronomy experiences. Expectation disconfirmation theory originated from marketing literature; it is a cognitive theory that seeks to explain post-purchase satisfaction as a function of expectations, perceived performance, and disconfirmation of beliefs (Oliver, 1980). It is specifically designated for customer satisfaction decisions, and it has been applied within tourism research to study tourist satisfaction (Chen et al., 2020; Coghlan, 2012; Correia et al., 2013).

In expectation disconfirmation theory, consumers are believed to form expectations of products or services before they purchase; the subsequent purchase of the products or services reveals the actual performance level, which is compared to expectation levels using a better than, worse than expectation labeled as negative or positive disconfirmation, and simply confirmation if as expected (Oliver, 1980). In our study, we considered online reviews of gastronomy experiences as both expectation forming and post-experience evaluation. Since online textual reviews are believed to reflect customers' experience and are generated by users voluntarily, it is used as a form to understand other customers' experience (Bi et al., 2019; Ye et al., 2014). Previous studies in tourism employed online reviews to explore important attributes (Xu & Li, 2016) and review sentiments in the context of Online Travel Agency (OTA) websites (Berezina et al., 2016). However, online reviews are less direct, and other information features such as price, review numbers, image features, and overall ratings are also important considerations for experience evaluation. In addition to this, as a P2P marketplace, it has a unique attribute compared to regular OTA websites, which is host information. Host credibility is discussed in associating with pricing (Tong & Gunter, 2020b), and it's considered a significant factor in travel product selection (Ma et al., 2017).Therefore, this study cooperates the number of years that hosts joined Airbnb as a form to represent host credibility and explores how it affects overall ratings.

2.5 Gastronomy post-experience evaluation: ratings and reviews

After participating in the gastronomy experiences, Airbnb enables gastronomy tourists to evaluate the experiences. People can voluntarily leave the reviews and rate the experiences, and ratings serve as a quantified overall evaluation after the experience (Nieto-Garcia et al., 2019). Ratings are commonly used to signal consumers' experiences and reflect satisfaction in various service sectors (Gao et al., 2018; Guttentag, 2015). However, star ratings are unlikely to reflect sufficient evidence in post-evaluation due to the nature of the ratings being number-based. In addition to this, the distributions of ratings arising on major review platforms tend to be overwhelmingly positive, missed with only a small number of highly negative reviews (Hu et al., 2009). Therefore, ratings and reviews complement each other and serve as important attributes in understanding the outcome of the experience. Thus, by factoring in online reviews and ratings, the study explored and examined the post-experience evaluation as a measure of satisfaction. Online reviews are always considered a significant driver of consumer behavior because they provide a convenient way for consumers to discover, evaluate, and compare products and services on the Internet (Zervas et al., 2021). Similarly, as a P2P platform such as Airbnb, online reviews provide more details on reflecting the experiences. Kwok et al. (2020)'s study proposed a 7P model for understanding Airbnb accommodation services. It summarized aspects that appear on Airbnb reviews from 7 elements: service products, price, place, promotion, participants, physical evidence, service process, and travelers. The model suggested that these seven elements are always appearing in the reviews as a reflection of the real experiences compared to promotional information, such as photos and related descriptions. Similarly, in addition to accommodation services, tourism experiences post evaluations work in the same way. Tourism experiences in the P2P marketplace are becoming the focal point for the growing tourism market; they are listed and organized by inspiring locals (experience creators) who host the events, aim to explore destinations and fill up curiosity (Ting, 2019). Therefore, online reviews for tourism experiences are essentially needed to explore an in-depth understanding of the satisfaction and dissatisfaction of post-experience evaluation. However, online reviews only reflect a part of the experience evaluation, which sometimes can lead to a biased conclusion. Online reviews and ratings are included in exploring post-experience evaluation and the influencing factors to form a holistic view of post-experience evaluation. Based on the aforementioned information, a construct of the model is represented in Figure 1.

Figure 3-1 **The proposed conceptual model of Satisfaction Disconfirmation at P2P marketplace**



3.Methodological procedures

This study used a combination of approaches, including big data analytic methods and a regression model, to uncover Airbnb gastronomy experiences and determine how the information affects travelers' participation in gastronomy activities. As far as the data, both textual data and photographic data were considered through analytic process. Gastronomy experiences based in the U.S. were selected as the United States is a destination with ethnic diversity, a great representation of international ethnic cuisine, and distinctive regional food characteristics (DiPietro & Levitt, 2019).

3.1 Data scraping

The data from this study is scraped from the Airbnb experiences website https://www.airbnb.com/s/USA/experiences, with a total of 196,265 reviews, 1,331 gastronomy experiences, and 1,331 featured photos. The scraped data information included in this study is publicly accessible. Therefore, there is no need for ethical clearance. The geographic location was set as the United States, and the activity time range was set from 2022, April 10 to 2023, April 10; a wide range of time selection (one year) is to capture the full spectrum of Airbnb experiences in "food and drink" category. Extracted data include activity descriptions under food and drink, price, rating, reviews, host information, and visual information URL on activities.

3.2 Data analysis

Mixed approaches consist of topic modeling, visual information characteristic effect, and OLS (Ordinary Least Square) model to analyze data. In the first stage, the tourists' reviews were extracted and performed topic modeling. We applied Latent Dirichlet allocation (LDA), a popular unsupervised machine learning technique that aims to find hidden structures within a large body. In the second stage, pictorial content on Airbnb gastronomy experiences was stored in URL format. Google Cloud Vision API was adopted to identify image features. Two of the identified features—colorfulness and the form of the visual elements (image and video form) were further integrated into the OLS model to understand how they influence post-experience evaluation: overall ratings. Lastly, in addition to image features, the OLS regression further considered reviews sentiment; TextBlob library was adopted to identify reviews sentiment. In addition, hosts' number of years' experience, neutralized comment count, and price was also considered. It is worth mentioning that in order to normalize the number of reviews considering time might be a variant, this study calculated the review rate based on average reviews per month since the experience was first listed. The same approach was taken in Barnes and Kirshner (2021)'s study.

3.2.1 Implementing LDA and sentiment analysis on tourists' reviews

User-Generated Content (UGC) is produced every day and fosters the increased unstructured data in the tourism and hospitality sector (Rosen & Purinton, 2004; Vu et al., 2019). Due to the features listed on Airbnb experiences pages, textual data such as online reviews are available in a large amount. For gaining a deeper understanding of a large volume of textual data, topic modeling has long been considered an effective tool in the tourism discipline (Jelodar et al., 2019; Vu et al., 2019). From a variety of topic modeling algorithms, Latent Dirichlet Allocation (LDA) is the most well-known and commonly used in literature (Jockers & Thalken, 2020). It is an unsupervised machine learning method that aims to classify corpus based on the similarities between documents, and it has been implemented by other tourism literature (Sutherland & Kiatkawsin, 2020). In this study, the Gensim Python toolkit was used to carry out the analysis for LDA. Before implementing the topic modeling, text pre-processing was conducted to clean the dataset; the steps were taken as follows: (1) removing stopwords, punctuations, numbers, single characters, and extra spaces; (2) converting text data to lower cases; (3) lemmatization and tokenization. Lemmatization and tokenization both have the same goal of returning the words' base form. WordNet lemmatizer and PorterStemmer were used in our study. Similarly, sentiment analysis was performed to understand the individual reviews' attitudes. TextBlob library was used to determine the dominant sentiment. It has been actively used to perform sentiment analysis tasks in tourism and hospitality literature (Ali et al., 2021). Polarity was calculated to identify the reviews' sentiment. In our study, since one Airbnb experience contained a number of reviews, the percentage of positive, neutral, and negative reviews count were used for building the Ordinary Least Square (OLS) model.

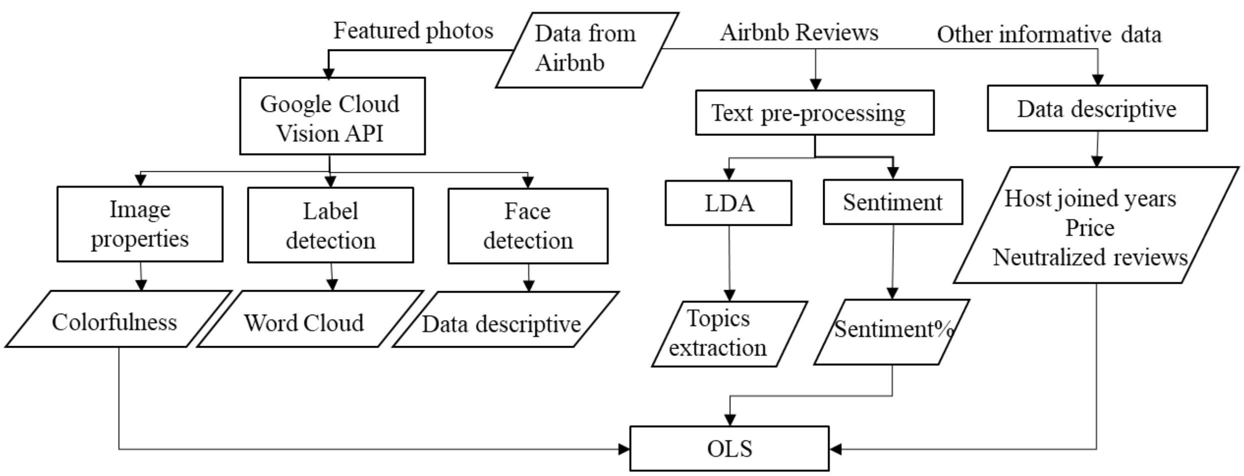
3.2.2 Implementing Google Cloud Vision API to extract image features

Our Airbnb gastronomy experience image dataset extracted the first photo that appeared on the experience page as our sample. Because they have higher visibility and they are considered more representable of the experience. Therefore, we used Google Cloud Vision API (available at https://cloud.google.com/vision/) to extract image features. In total, three functions were adopted. First, the API's "image properties" function allows us to identify the image's prominent colors as RGB values and percentages of the overall pixel count. Based on the pixel count, we calculate the sum of the top three colors' pixel percentage, where the lower top three colors' pixel percentage indicates the image is colorful, and the higher indicates the image is not colorful. Second, "label detection" function allows for identifying objects on the image. Third, the "face detection" function was used to determine whether at least one human face is present in the image. Additionally, with the advanced function of the Airbnb experience, it allows hosts to post a video instead of a photo as the featured visual illustration. From the sample, there are, in total, 116 experiences used videos among 1,331 experiences. Therefore, we selected the first photo after the video as the photo sample.

3.2.3 Ordinary Least Square (OLS)

The OLS model was used to test relationships in the proposed conceptual model, and results from previous steps were utilized to compile the model. Since all the variables are continuous and explanatory, it can effectively estimate the unknown parameters for the collected arbitrary dataset. Therefore, OLS was used to explore and analyze the relationships in the proposed construct below. We considered the number of years joined Airbnb to reflect host credibility, colorfulness as an image attribute, reviews sentiment, and price (i.e., the independent variables) to assess the relationship with experience ratings (i.e., the dependent variable). Figure 2 is a flowchart demonstrating the mixed approaches taken in our study. Python was used for all the analyses.

Figure 3-2 **Flowchart of mixed methods approach.**

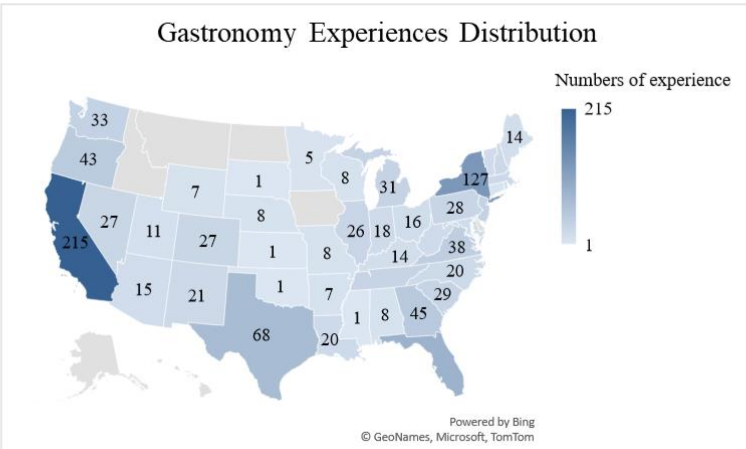


4. Results

4.1 Data overview and description

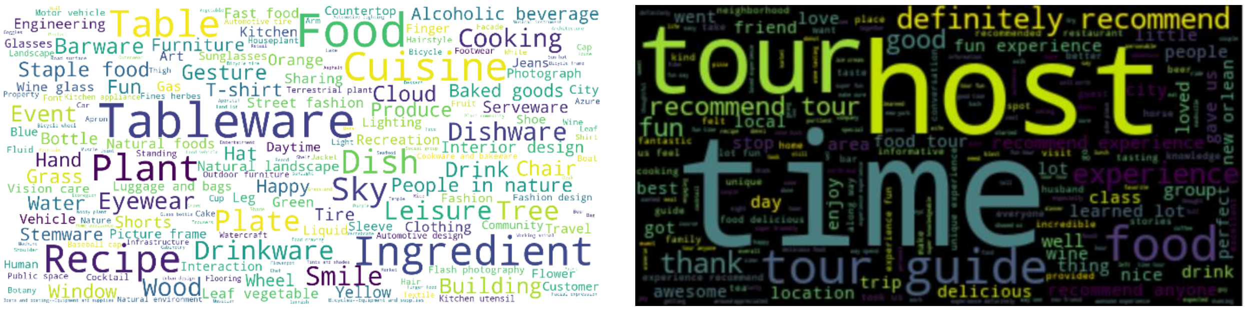
A total of 1,331 gastronomy experiences were collected as the sample, with 1,331 photos and 196,265 user-generated reviews. Figure 3 demonstrated the distribution of the gastronomy experiences within the U.S., where California state had the most gastronomy experiences (215) among all other states. Followed by the state of New York (127) and Texas (68). In addition, the average price of gastronomy experiences was 98 U.S. dollars, and the average host experience (number of years joined Airbnb) was 5.2 years. As far as the neutralized reviews, the average neutralized the number of reviews was 7.1.

Figure 3-3 **Gastronomy experiences distribution**



As for image attributes, along with image properties, label detection, and face detection were two functions that gain a deeper look into the images. From the Google Vision API results, among 1,331 photos, 918 photos contain at least one human face, indicating that human faces were present in the majority of the gastronomic experiences. It could be because human interaction with food elicits higher levels of interest from potential consumers. When it comes to image properties, the average pixel percentage from the top three colors is 40%. In terms of label detection results, a word cloud was developed to display the produced labels to better visualize them. In the same way, we constructed a word cloud to illustrate the summary of online review data. In figure 4, two-word clouds were displayed for better visualization of data description. 4a demonstrates the overall image labels, where it is clear that “Tableware,” “Cuisine,” “Food,” “Ingredient,” “Recipe,” and “Plant” appeared more frequently in the detected labels. 4b demonstrates the overall representation of online reviews. From the online review word cloud, it is clear that “time,” “host,” and “tour” appear in a bigger size, which means they have a higher appearance, among other words.

Figure 3-4 **word clouds.**

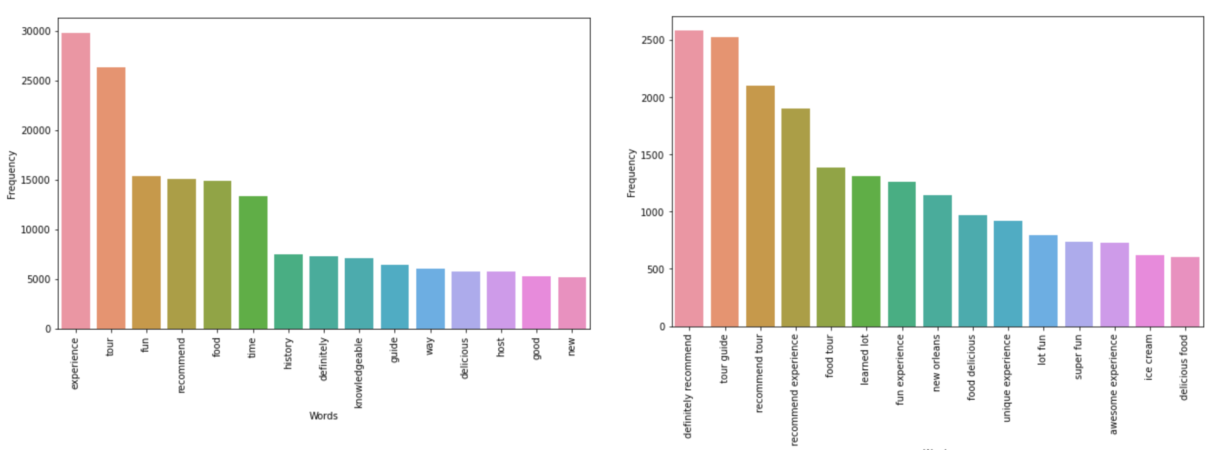


4a. Image labels word cloud

4b. Online reviews word cloud

After text pre-processing, we built a unigram and a bigram with the top 15 words/terms, which exhibited a series of one and two adjacent words from a string of tokens for better visualization. Words such as “experience,” “tour,” “fun,” and “recommend” appeared more frequently in unigram. Similarly, phrases conveying experience, recommendations, and food were used more frequently in bigram. In addition, words associated with the host, such as “tour guide,” appeared more frequently. New Orleans also appeared in the top 15 phrases, indicating its status as a food city. Please see **figure 5** for more details.

Figure 3-5 **Top 15 words frequencies: unigram and bigram**



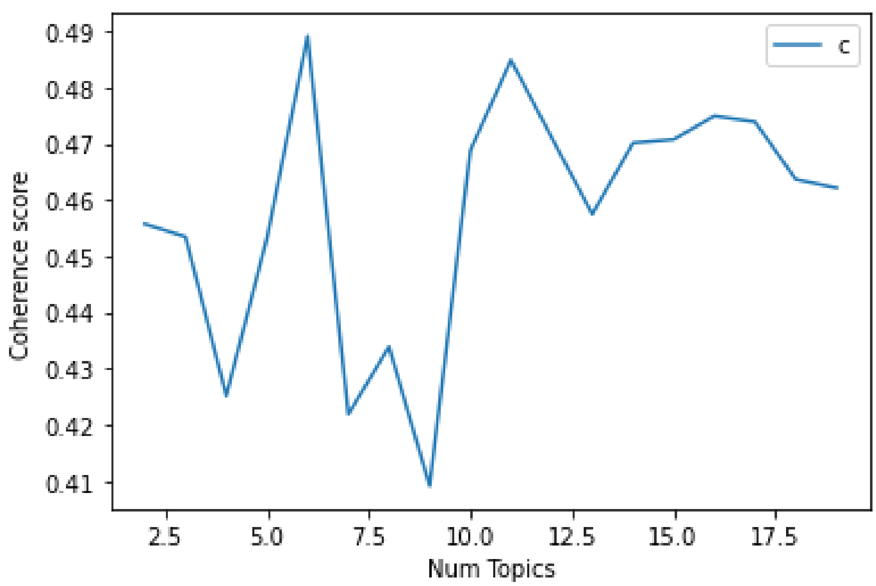
5a. Unigram for online reviews 5b. Bigram for online reviews

4.2 LDA analysis results

4.2.1 Optimal number of topics

Multiple models with different k values were created to determine the optimal number of topics (k from 1 to 20). Based on the quantitative index of model fit (i.e., coherence scores), we selected k = 6 because it has the highest coherence score (0.489) and corresponding perplexity of -18.075. Coherence scores are commonly used to determine the best number of topics and evaluate the quality of the model (Mimno et al., 2011; Syed & Spruit, 2017). The higher the coherence score, the better the model fit, whereas the lower the perplexity, the better the model fit. Figure 6 plotted coherence scores with the number of topics.

Figure 3-6 **Coherence scores with number of topics.**



4.2.2 Identified topics distribution

From the online reviews, six major topics emerged within the reviews including (1) food city tour, (2) social interactions, (3) host, (4) local food culture, (5) beverage appreciation, (6) hands-on learning, the order is based on the percentage of tokens indicating the topic importance. "Food city tour" contained context describing food as well as the city. It is one of the most common food activities in food tourism (Du Rand & Heath, 2006). "Social interactions" is the topic containing reviews describing interactions with friends, social groups, and people who participated in the same experience. "Host" emerged as an important theme in gastronomy experiences, with implications for the 'host-guest encounter' and the role of "services" in the Airbnb user experience. "Local food culture" included reviews describing the local food cultural elements, stories representing food authenticity, and food cultural anthropology. The topic "beverage appreciation" is mostly involving tasting experiences, such as winery or distillery tasting. The experiences reflect sensory evaluations and critics (Siegrist & Cousin, 2009). Lastly, the "hands-on learning" topic contained reviews that describe a learning experience with food. The common ones are cooking classes, by exploring different ingredients, recipes, and learning to make food. To gain a better insight, table 1 displayed the top 20 frequently occurred terms within each topic.

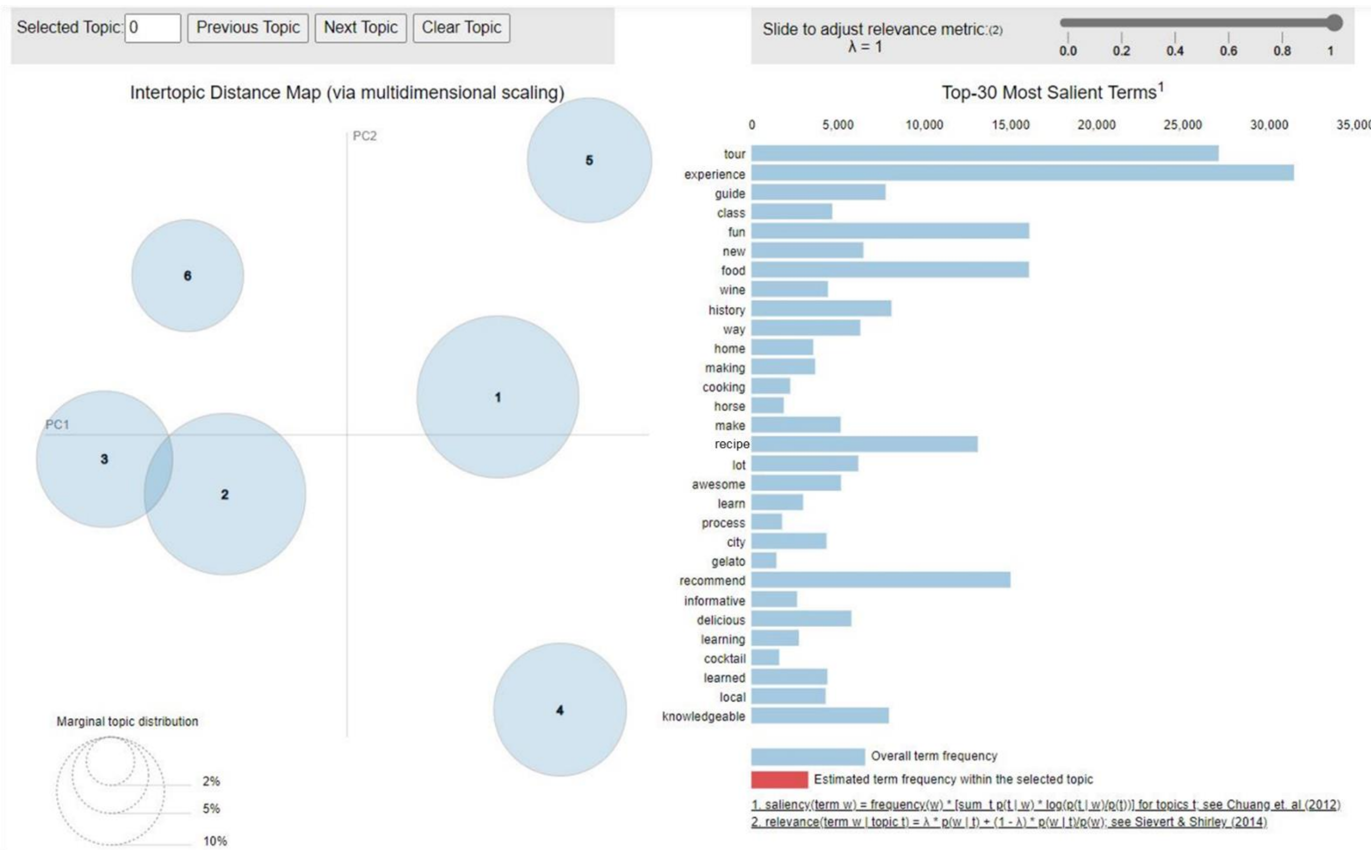
Table 3-1 **Top 20 frequently occurred terms in each topic**

Topics	Percentage of tokens	Top 20 terms
food city tour	22.5%	tour+ fun+ food+ guide+ recommend+ knowledgeable +lot+ time+ good+ awesome+ informative+ place+ delicious+ learned+ history+ loved+ city+ worth+ different+ way
social interactions	22.4%	experience+ time+ recommend+ fun+ definitely+ host+ friend+ feel+ loved+ home+ thank+ comfortable+ unique+ perfect+ knowledge+ making+ trip+ husband+ everyone+ group

host	15.9%	experience+ new+ way+ fun+ recommend+ host +learn+ awesome+ people+ time+ friendly+ lot+ must+ trip+ definitely+ see+ history+ worth+ cool+ local+ fantastic
local food culture	15.1%	tour+ history+ food+ recommend+ local+ story+ experience+ guide+ city+ place+ knowledgeable+ area+ new+ time+ evening+ excellent+ beer+ bar+ drink+ restaurant
beverage appreciation	13.3%	wine+ group+ experience+ time+ tasting+ jack+ rum+ biscuit+ conversation+ ride+ tour+ good+ nice+ drink+ people+ baguette+ winery+ food+ easy+ fun
hands on learning	10.7%	experience+ class+ make+ food+ delicious+ home+ cook+ learn+ process+ fun+ gelato+ chef+ recommend+ dish+ ingredient+ meal+ recipe+ ramen+ kitchen+ love

Apart from the Gensim library, the pyLDAvis package was used to understand the generated topics and show how well the LDA model fits across subjects and words (Sievert & Shirley, 2014). Interactive visualization is created using the developed LDA model, the corpus of terms, and their frequencies of occurrence in the review document. As a result, this visualization is demonstrated below in figure 7. On the left side of the figure, the size of the circle or the bubble represents a topic's importance in the document. The larger the bubble, the higher the topic's importance. The distance between the circles or topics represents their inter-similarity. Circles representing topics 2 and 3 are overlapping, depicting similarities between them. A poor topic model would have numerous overlapping circles concentrated in any one quadrant of the chart. On the right side, for each topic, the top 30 most relevant terms with estimated term frequency within this topic. The constituent words are depicted in a histogram and get highlighted when a particular topic is selected. Please see more details in the appendixes for each topic.

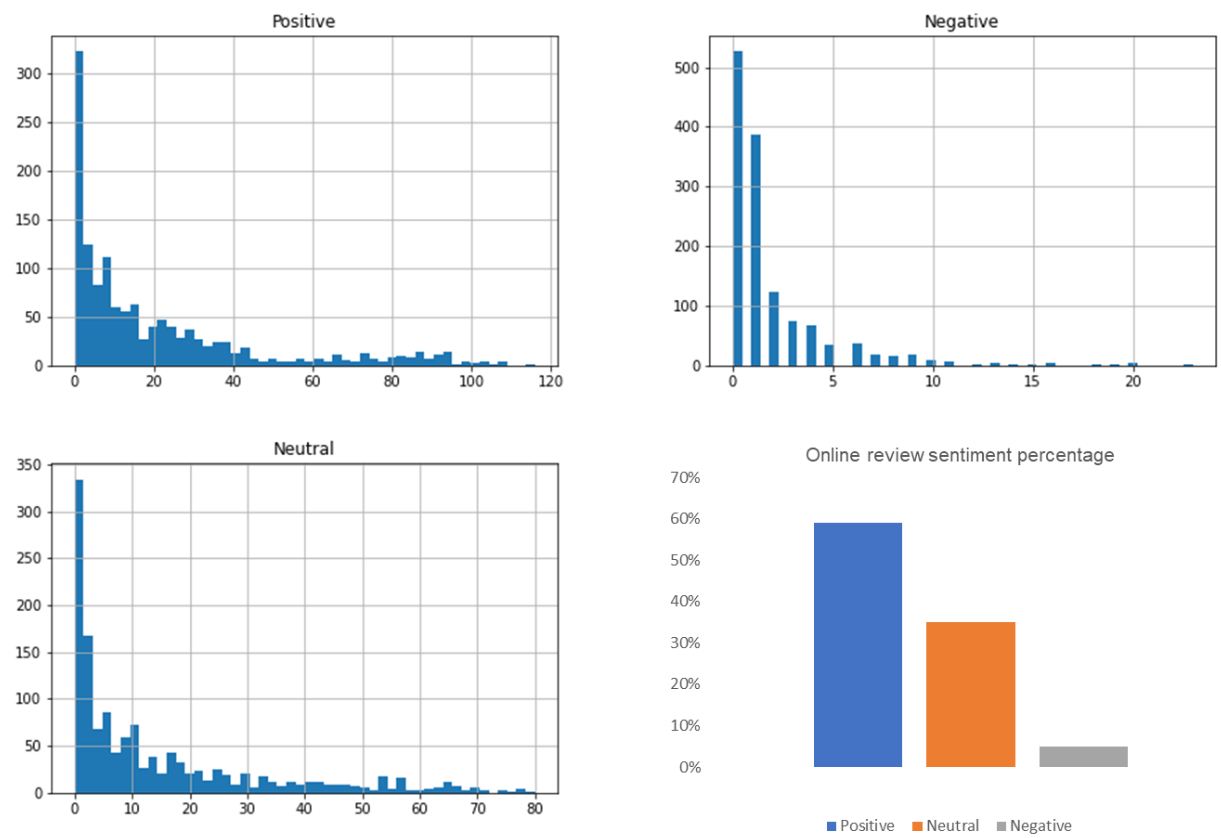
Figure 3-7 **Inter-topic distance map**



4.2.3 Sentiment analysis results

Sentiment analysis is a comment practice in understanding reviews sentiment. In our study, sentiment analysis was performed to determine the sentiment of the reviews, and the results were used to further implement into OLS regression. TextBlob, a library for Natural Language Processing, was used to achieve the analysis goal. The polarity for the sentiment from negative to positive is [-1,1]. In our study, the score was set at negative<0, neutral==0, and postive>0. Since each of the experiences has multiple reviews, we decided to include the count of positive, negative, and neutral reviews in each experience and remove the experiences with 0 reviews. Therefore, the number of gastronomy experiences was reduced to 1,224. Figure 8 demonstrates the distribution of positive, negative, and neutral reviews and also the proportion of three sentiments. The majority of the sentiment is positive (59%), followed by neutral reviews (34%) and negative reviews (5%). Please see details in Figure 8.

Figure 3-8 **Distribution and percentage of online reviews sentiments.**



4.3 OLS analysis results

Ordinary Least Square (OLS) regression was conducted to understand the association among host credibility indicators (years of experience with Airbnb), colorfulness, review sentiments, normalized review count, price, and the overall ratings of the gastronomy experiences. First, we examined multicollinearity among variables and used Variance Inflation Factors (VIFs) as measures. Values of VIFs are all below 4, which indicated no multicollinearity issue with variables, and correlations between variables would be acceptable (O'brien, 2007). Table 2 demonstrates VIFs value in detail. Overall, the adjusted R2 goodness of fit measure reached 0.906, indicating the model represents a high proportion of variance explained.

Table 3-2 **Variables Variance Inflation Factors.**

Independent Variables	VIF
Years of experience with Airbnb	3.43
Colorfulness	2.95
Positive sentiment	1.89
Negative sentiment	2.99
Neutral sentiment	3.86
Neutralized review count	1.31
Price	1.76

In the OLS regression, the coefficients measure the influence of the regressors on the dependent variable (Hayes & Matthes, 2009). The regression results show that the coefficient of years of experience with Airbnb is significantly positive (β = 0.319, p < 0.001), which indicates host years of experience have a positive effect on ratings. Colorfulness is the percentage of the pixel on the top three colors, and it has been shown to positively influence ratings (β = 0.041, p < 0.001). As far as the sentiment, percentages of each sentiment in a gastronomy experience were used to build the model; only positive sentiment (β = 0.018, p < 0.001) and negative sentiment (β = -0.067, p < 0.001) showed significant effects on gastronomy experiences overall ratings, where positive sentiment has a positive influence, and negative sentiment has a negative effect on ratings. Lastly, both neutralized review count (β = 0.006, p < 0.001) and price (β = 0.005, p < 0.001) have positive influences on ratings.

Variables	Beta	Std. Error	t-value	Sig.
Years of experience with Airbnb	0.319	0.013	24.461	***
Colorfulness	0.041	0.002	26.986	***
Positive sentiment	0.018	0.002	10.486	***
Negative sentiment	-0.067	0.021	-3.146	***
Neutral sentiment	0.024	0.004	0.662	Not supported
Neutralized review count	0.006	0.002	2.642	***
Price	0.005	0.000	14.193	***

5. Discussion and conclusion

5.1 Research findings

The main contribution of this study is that it has taken a mixed-method approach in understanding gastronomy experiences post evaluation of the P2P platform (i.e., Airbnb). Our research focuses on three areas of findings to explore post-evaluation and factors that might be influential to post-evaluation. First, our study examined 196,265 online reviews and used topic modeling to identify the major themes. The results have shown that LDA effectively identified six topics across all the reviews, which are (1) food city tour, (2) social interactions, (3) host, (4) local food culture, (5) beverage appreciation, (6) hands-on learning, ranked by topic importance. Among six aspects, four topics are directly related to food and drink, reflecting gastronomy experiences, whereas two topics are mainly related to people, social interactions and hosts. Due to the nature of the gastronomy experiences involving interaction with a group of people, social interaction becomes one of the possible social motives for attending gastronomy experiences (Tikkanen, 2007). People who participate in the gastronomy experiences can fulfill their social needs and understand the experience co-creation process (Everett, 2012). Tourists instinctively factor these interactions into their post-evaluation in the form of online reviews. As for hosts' evaluation, the finding aligned with previous literature in discussing Airbnb accommodation services, where hosts play a significant role in trust establishment, reputation, and relationship building (Cheng & Jin, 2019; Moon et al., 2019; Zervas et al., 2021). Not to mention the nature of P2P business models require more interpersonal communication with hosts, where the hosts' trustworthiness and personal identity, attitude, and personality significantly influence post-experience evaluation (Bridges & Vásquez, 2018). Apart from these two topics, the rest of the four topics are related to unique food and beverage experiences, food culture anthropology, and heritage. Interestingly, from these topics, reviews emphasized learning as the main objective, implying that tourists today have an increased awareness of pursuing food as a linkage to local heritage and cultural authenticity. This finding aligned with previous literature discussion on how gastronomy experiences in a tourism destination provide a "sensory window into culture, history and people of a place"; and how it benefits local culture and identity (Kim & Ellis, 2015; Ottenbacher & Harrington, 2013). Therefore, the results from LDA addressed the first research question and gained a holistic view from online reviews of gastronomy experiences. As online reviews are considered critical post-experience evaluations, the results provide insights into what are the aspects people tend to emphasize when evaluating gastronomy experiences.

The second aspect of findings mainly addressed the second research question, where visual elements are taken into consideration. It is discussed in the previous literature that visual illustrations, such as photos and videos, are essential for online food tourism marketing because it sets expectations for tourists (Horng & Tsai, 2010). The information displayed through the website and the way how online platform presents graphics and photos influence the viewers' perception(Rosen & Purinton, 2004). In our study findings, the majority of the photos (69%) contain at least one human face. The main reason might be that for gastronomy experiences, it is easier to imagine oneself in an environment by viewing the photos with people. In a social media setting, it has been discussed that photos with faces engage people more (Bakhshi et al., 2014). The same idea works for online tourism marketing, where Deng and Liu (2021) discovered over 50% of user-generated photos contain tourists' faces, and photos with faces have a direct impact on tourists' gaze. In addition to this, "colorfulness," as an important image attribute, was found significantly influence ratings of gastronomy experiences. Therefore, our study findings contribute to the hospitality and tourism literature by exploring the effect of the image attribute on post gastronomy experiences evaluations.

Third, the findings from OLS regression demonstrated the factors that have significant impacts on gastronomy experiences ratings. From the results, we discovered host years of experiences, colorfulness, and neutralized review count all have a significant positive influence on ratings. Since the Airbnb experiences sector doesn't contain information such as SuperHost badge or host experiences count, therefore, host years of experiences became the available information to indirectly reflect the host's credibility. In Zhu et al. (2019)'s study, under Airbnb accommodation service, the relationship between host experiences and satisfaction was explored, and the findings indicated that the experience of the hosting negatively influences users' satisfaction. The measures of hosting experiences in Zhu et al. (2019)’s study contain host duration, host listings count, and the number of reviews. In our study, since Airbnb experiences don't have hosts' listing count, the count for the number of reviews was neutralized and used as a separate measure for experiences popularity, the results of host years of experiences implied differently, and it positively influenced ratings. Different conclusions might be caused by different service sectors (Airbnb accommodation V.S. Airbnb experiences) where the products are transitioned from a comfortable stay to a memorable experience. For Airbnb experiences, hosts play an entirely different role, similar to the tour guides. Throughout a gastronomy experience, frequent interactions with tourists are required. Hence, years of experience might reflect on the quality of the service. Consequently, tourists value hosts with more experiences, and the hosts' years of experience positively influence ratings.

In addition, colorfulness as an image attribute positively impacts the ratings, which implies that less colorful leads to higher ratings. Because colorfulness is the pixel percentage of the top 3 colors, the higher the percentage means the less colorful. This finding aligned with Barnes (2022)'s study, where in this study, the researchers assessed the color palette simplicity and found that color coherence and color palette simplicity lead to higher satisfaction in the context of service marketing. Both our findings and Barnes (2022)'s study finding supported Gestalt theory, where in marketing and design, consumers prefer images that use a smaller number of colors (Deng et al., 2010). As far as review sentiments, our study found that positive and negative sentiment impact ratings in positive and negative directions, whereas neutral sentiment doesn't impact ratings in a significant way. This finding aligned with Tian et al. (2021)'s study, where they took an interest in restaurant online reviews sentiments and explored the impact of ratings. In our study, from the sentiment analysis results, although the majority proportion of the reviews is positive on Airbnb, it doesn't mean negative sentiment reviews have less impact on satisfaction. The OLS results demonstrated that both negative and positive sentiments are essential for tourists' ratings.

5.2 Theoretical and practical implications

Theoretically, this study contributes to the existing literature on gastronomy experiences through the P2P platform, using Airbnb experiences as the source of data, and sheds light on the merging and rapidly developed P2P new service sectors. Airbnb experiences as a relatively new business sector representing P2P tourism service expansion. Therefore, this is one of the first studies exploring tourism experiences provided through P2P platforms and evaluating the impact of both textual data and image data on gastronomy experiences. In addition, methods-wise, by using big data analytic methods and OLS regression, the investigation develops a rigorous research process for analyzing post-experience evaluations. More specifically, this study first analyzed a large number of online reviews and contributed to the current gastronomy tourism literature by identifying the six major topics through topic modeling LDA. Some important factors in the accommodation service sector are less relevant to gastronomy experiences compared to Cheng & Jin's (2019) study findings. For instance, location is no longer a relevant topic from our findings. Instead, people care more about social interactions, hosts, and related food or drink themes.

Second, the integration of the colorfulness attribute makes a contribution to understanding the importance of images in post-experience evaluations and explores how it is relevant to overall ratings. In addition, from the label detection, the word cloud provides an overview of what are some objects frequently displayed. Although there is some limited understanding of the visual information impact from other image attributes (e.g., specific hues, saturation), the results of the our study generally support a body of research examining Gestalt theory in design (Barnes, 2022; Schloss & Palmer, 2011; Wei et al., 2014). More importantly, it provides a trait of thoughts for future research on how to integrate image characteristics into research.

Third, through a combination of big data analytics (e.g., topic modeling, sentiment analysis, image analysis) and traditional methods (i.e., OLS regression), this study identified factors that are related to gastronomy experiences post evaluation. Theory wise, it employed the expectation disconfirmation theory in the context of P2P gastronomy tourism experiences. The theory guides this study in forming the research framework and factors that can influence post-evaluation: ratings, reflecting satisfaction. In detail, unique factors such as colorfulness, online review sentiments, and host experiences were not explored in understanding expectations and perceived disconfirmation in previous food tourism studies to our best knowledge. We also included other factors that are commonly believed to influence ratings (e.g., price, neutralized number of reviews) and explored their relationships with overall ratings, which again supported the wide application of expectation disconfirmation theory in tourism and hospitality literature.

Practically, the six topics identified from gastronomy experiences online reviews indicate the aspects that tourists care about. Clearly, tourists talk about human interactions with others and appreciate a good learning experience involving food cultural anthropology. Service providers and the P2P platform may greatly benefit from this by catering to tourists' needs. For the hosts and service providers, additional interactions with the tourists are encouraged during the gastronomic experiences for them to embrace authenticity and increase local culture knowledge, be excellent storytellers, and bring the experience to life. Additionally, it is not necessary to include photos that are too colorful. Compelling photos tend to be less colorful and more coherent. As for price, price's positive impact on satisfaction also implies that tourists are willing to pay more for great services. Therefore, service providers should pay attention to creating interactive environments, providing learning experiences, and listing less colorful photos.

As for P2P platforms like Airbnb, in promoting gastronomy experiences, additional information can be added on the experience page to help tourists make decisions. It would be great to include the hosts' styles, strengths, and experiences as a part of the homepage description since hosts play an even more important role in organizing and facilitating compared to accommodation services. In addition, a co-creation experience involves additional interactions and efforts from organizers; therefore, keywords such as "engaging," "great chance for social interactions," "knowledgeable," and "fascinating food culture stories" can be some of the hosts' keywords to display on the page. Moreover, platforms can encourage Airbnb hosts to enhance their information page by providing suggestions based on this study's findings, such as how to set up effective photos, what to include in gastronomy experiences creation, and what tourists care about when participating in these experiences.

5.3 Limitations and future works

Our study has serval limitations. First, the study data is based on the U.S. market from food and drink experiences through Airbnb. Future research can include a bigger scope geographically and more data sources to test the results. Second, colorfulness only represents one aspect of the image; although we were able to gain some insights from face detection and label detection results, to explore the influence of images fully, more aspects of image attributes should be considered, such as saturation, hues, and harmony. In addition, future research could also consider evaluating the effectiveness of videos and photos since this can be a variance in tourists' perceptions. Third, in our study, the sentiment analysis was developed to support OLS regression; therefore, we didn't go in-depth and explore the topics on each sentiment. Future studies can consider including topic modeling to explore more on each sentiment. Fourth, we only included the length of hosts' experiences as an indicator of the hosts' credibility in understanding overall ratings and didn't include the exploration of host profiles. For the accommodation service sector, studies were conducted on perceived trustworthiness and credibility (Ma et al., 2017). However, the linguistic manifestations of host profiles in understanding credibility perceptions under gastronomy experiences remain a gap. Thus, future research could explore Airbnb experiences' host profiles and investigate their impact on tourists' perceptions.

Chapter 4 General Conclusions

1. Overall conclusion

This article-based dissertation conducts three separate studies related to discovering the role of visual information in tourism and hospitality field of studies. The overall purpose of this dissertation is to (1) synthesize and summarize the hospitality and tourism literature that are related to visual information using machine learning, (2) to investigate the decision-making process and understand the role of images during gastronomy pre-experiences, (3) to explore gastronomy post experience evaluation and gain insights on the factors that can influence the post experience. To fully expand on this topic, three independent papers separately addressed each one of the aspects, achieve a coherence understanding of the visual information importance in hospitality and tourism field.

Owing to the development in algorithms, researchers outside of data science are able to explore unstructured data (e.g., image data). The growing literature in marketing and business research further validate the idea of the importance in cooperating image data. In terms of tourism and hospitality research, there is still substantial room for practical and theoretical advancement in this important field. This is also the main motivation behind the overall purposes of this article-based dissertation. The next three sub-sections of the conclusion chapter will briefly summarize the theoretical and practical implications of the three papers. These summaries are purposely brief, since each article has already presented an in-depth conclusion within its appropriate section.

2. Brief conclusion from each study

The first paper, "*visual information analysis in hospitality and tourism applying machine learning: a systematic literature review from a text mining approach*," aims to review, analyze, and synthesize visual content analysis in tourism and hospitality research. The relevant papers were collected from both journals and conference proceedings to perform a systematic literature review. The paper first discussed the overall research that has been conducted over time on visual information analysis applying machine learning techniques in hospitality and tourism disciplines and introduced the evolution of machine learning algorithms. Second, the citation network analysis of the identified literature and references was conducted to reveal influential papers. Third, this study used a text mining technique to identify topics through applied text clustering analysis to add in-depth discussion on selected papers. the results included a longitudinal overview of identified papers and elaborated on data analytic approaches in the existing literature.

A citation network specified 10 communities with majority papers, whereas text clustering results identified 7 topics. This discrepancy was due to the similarity of clusters 1 and 2, which both referenced geo-tagged photos. Similarly, cluster 5 and cluster 10 shared a similar topic, understanding social media marketing. In the identified topics, CES and photos aesthetics were considered as one topic. Although CES has a broader definition and greater meaning than photo aesthetic, in hospitality and tourism visual information literature, CES is discussed as aesthetic appreciation for surroundings, including cultural heritage and nature. Importantly, consumers' destination images can be evaluated from UGC, and the discussion on destination image is no longer limited to survey data. Furthermore, the negativity of consumers' destination image can also be evaluated by incorporating satellite images and geo-tagged photos and by conducting time-series studies.

The second paper, "*Standing out from the crowd: exploring online information cues on Airbnb gastronomy experiences*," aims to explore the decision-making process and understand what factors influence the consumer decision the most. This paper employed a mixed-method approach, combined with data mining and experimental design. In detail, this study first mined Airbnb gastronomy experiences data from the website and, according to the real data, formed reasonable levels based on each information cue. Next, the survey was designed incorporating six identified information cues at different levels, and survey data were collected from tourists. Choice-based conjoint analysis was performed to understand the importance at the information cues level and to explain tourists' online information process. This research makes several contributions. Theoretically, it employed signaling theory and a systematic heuristic model in explaining how tourists process online information. It successfully bridges the gap by introducing promotional photos and host credibility information cues in an experimental study. Methodologically, the text mining approach was taken in information cues segmentation, which serves as a solid foundation for conjoint analysis survey design. The survey-based conjoint analysis further identified important information cues to each level and provided insights into each market segment. The findings provide substantial practical implications for marketers, and host credibility, image, and price are the three most important attributes when people make decisions. In addition, the finding enhanced the concept of trust and credibility and the role they play in consumer selection on the P2P platform. From the aspect of the featured image, the indoor group activities image category is the most popular selection. It might be consumers prefer to learn about their surroundings more and picture themselves in the activities. They want to have a sense of what they are paying for as intangible and tangible services. Therefore, they prefer to see images of indoor group activities to gain a sense of interaction among the tour groups and hosts.

Lastly, the third paper, "*Exploring post-experience evaluation of gastronomy tourism experiences through Airbnb*," has two main objectives. First, it investigates the tourists' reviews through Airbnb and explores the meanings and patterns behind the reviews to understand post-experience evaluation. Second, it aims to discover what information is displayed and how they influence satisfaction. The study employed a mixed-method approach, combined NLP and regression in evaluating post gastronomy experience evaluation, and explored the factors that might have an impact on the post-evaluation. Theoretically, the study employed satisfaction disconfirmation theory and proposed a theoretical framework to investigate the gastronomy experiences on the P2P platform.

The third paper focuses on three areas of findings to explore post-evaluation and factors that might be influential to post-evaluation. First, our study examined 196,265 online reviews and used topic modeling to identify the major themes. The results have shown that LDA effectively identified six topics across all the reviews, which are (1) food city tour, (2) social interactions, (3) host, (4) local food culture, (5) beverage appreciation, (6) hands-on learning, ranked by topic importance. Second, through image analysis, this paper discovered the majority of the photos (69%) contain at least one human face. The main reason might be that for gastronomy experiences, it is easier to imagine oneself in an environment by viewing the photos with people. In addition, from Ordinary Least Regression, colorfulness attributes were taken into consideration, and the results indicate that colorfulness hosts' years of experience, review sentiment, and price all significantly influence the gastronomy post-experience evaluation.

Interestingly, the finding indicates that as far as promotional images, less colorful achieve a higher post evaluation. It aligns with Barnes (2022) 's study, where in this study, the researchers assessed the color palette simplicity and found that color coherence and color palette simplicity lead to higher satisfaction in the context of service marketing. Both our findings and Barnes (2022) 's study finding supported Gestalt theory, where in marketing and design, consumers prefer images that use a smaller number of colors (Deng et al., 2010).

Overall, three studies provide different aspects of insight on incorporating visual information in tourism and hospitality research. Other than the first systematic literature review, study 2 and study 3 are all based on gastronomy experiences from P2P platforms (i.e., Airbnb). Both study findings emphasize the importance of host credibility from a co-creation experience perspective, regardless of pre- and post-experience stages. In addition, from the image, two studies gain insights into the importance of interactions and the aesthetic value of simplicity. Moreover, the findings have practical implications in web design/display for platforms such as Airbnb. Platforms can encourage hosts to enhance their information page by setting up effective photos, be more interactive in gastronomy experiences design, and gain insights into what tourists care about when selecting and participating in these experiences.

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