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Research Paper

From Data to Policy Integrating Spatial Clustering and Digital Sentiment Analysis for Urban Tourism Planning

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Abstract

This study aims to identify spatial patterns of artificial tourist attractions and extract key visitor concerns to support urban tourism planning. To achieve this objective, spatial clustering and sentiment analysis were applied sequentially as complementary analytical approaches. The DBSCAN algorithm was used to group 62 artificial tourist attractions into five spatially coherent clusters based on geographic proximity. In parallel, Natural Language Processing (NLP) techniques were employed to analyze 2,800 online visitor reviews and classify dominant sentiment themes. The results reveal distinct spatial structures of attractions and recurring negative issues related to pricing transparency, parking availability, food quality, accessibility, and facility conditions. Using Batu City, Indonesia, as a case study, this research demonstrates how integrating geospatial analysis with user-generated content can transform informal digital feedback into policy-relevant insights. The proposed framework offers a practical, data-driven approach for informing tourism governance and planning decisions in emerging urban tourism destinations.

Keywords: Spatial Clustering; Digital Sentiment; Urban Tourism; Machine Learning; Policy Insights.

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1. Introduction

Tourism development in secondary and medium-sized cities increasingly shapes spatial growth, infrastructure performance, and visitor experiences worldwide (Manosuthi, 2024; Săvan et al., 2024). The rise of artificial tourist attractions—engineered leisure environments designed for commercial and recreational purposes—has been particularly notable across Southeast Asia, Latin America, and parts of Africa (Cardoso da Silva et al., 2024). Because these attractions frequently emerge outside established cultural or heritage frameworks, they introduce governance challenges related to spatial equity, service provision, and planning resilience (Xie, 2022). At the same time, tourism in secondary cities contributes to economic diversification, social inclusion, and improved place reputation (Maimaitiaili, 2024; Manosuthi, 2024). Yet local governments often struggle to manage this growth due to fragmented institutional arrangements and the absence of effective feedback systems (Maimaitiaili, 2024).

In urban areas such as Batu, East Java, the rapid proliferation of artificial attractions illustrates these governance tensions. While the sector expands in response to market demand, spatial management and public input mechanisms remain weak (Sulistyowati et al., 2024). The uneven dispersion of these attractions and the variability of visitor experiences create challenges for equitable development, public service delivery, and long-term planning capacity (Shim et al., 2022; McLoughlin & Hanrahan, 2023 Hudayberganov et al., 2024). This has intensified the need for data-driven tools that can reveal spatial patterns and systematically capture visitor perceptions.

The growing use of digital platforms such as Google Maps has introduced an important layer of participatory data (Frenzel et al., 2022). Online reviews now serve as informal channels for expressing satisfaction, concerns, or service gaps—especially in contexts where formal reporting mechanisms are limited (Sinanan & Ritter, 2024); Druker Shitrit & Noy (2024). These user-generated expressions provide rich qualitative insights that can uncover socio-spatial inequities and strengthen adaptive planning practices (Çakar, 2023); Akkaya et al., 2024). Meanwhile, methodological advances in Natural Language Processing (NLP) have made large-scale sentiment extraction increasingly feasible, and spatial clustering techniques are widely used to understand geographic patterns. However, despite the growing interest in these tools, few studies have integrated spatial clustering and sentiment analysis within a single analytical framework for tourism policymaking (Huang & Liu, 2024). Existing works tend to examine spatial distribution or online sentiment separately, which limits their ability to inform comprehensive planning strategies. Furthermore, artificial attractions—unlike natural or heritage sites—often lack established guidelines, requiring dedicated analytical attention (Nag, 2024); Karayazi et al., 2022).

This study addresses this gap by integrating the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm with sentiment analysis of Google Maps reviews using NLP techniques. By combining geographic proximity with the evaluative content of visitor feedback, the research aims to identify the spatial patterns of artificial attractions, extract sentiment-based issues raised by visitors, and translate these integrated insights into policy-relevant directions for tourism governance. Batu City—an urban area driven by tourism and characterized by heterogeneous spatial development—offers a suitable context to explore how informal public responses can be aligned with spatial analytics to strengthen planning decisions (Widi Lestari et al., 2023). Through this approach, the study contributes a methodological framework that links geospatial clustering and user-generated content, provides empirical evidence on how digital feedback can complement formal planning tools in secondary cities, and advances ongoing discussions on adaptive, data-driven tourism planning under conditions of spatial and institutional uncertainty.

2. Methods

This study adopts a mixed-methods spatial approach that combines clustering algorithms and Natural Language Processing (NLP) techniques to extract policy-relevant insights from artificial tourist attractions in Batu City. The analysis consists of four stages: defining the study area and collecting data, performing spatial clustering using DBSCAN, conducting sentiment analysis of visitor reviews, and extracting actionable policy recommendations.

2.1 Study Area and Data Collection

The spatial scope of Batu City, a medium-sized urban area in East Java, Indonesia, is characterized by its strong dependence on urban tourism and the rapid expansion of artificial attractions (Widi Lestari et al., 2023); Larasati et al., 2020). A total of 62 artificial tourist destinations were identified using Google Maps and cross-validated with official tourism portals and government directories. Geographic coordinates for each site were collected and mapped using GIS tools to establish the spatial basis of the analysis.

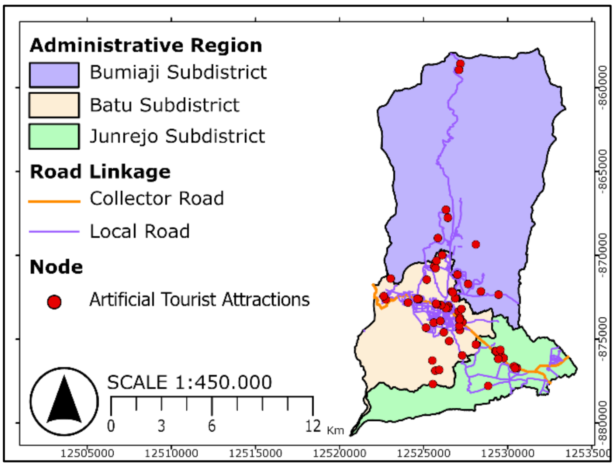

Figure 1. Scope of Batu City

Figure 1 presents the administrative boundaries of Batu City and the mapped distribution of 62 attractions across Batu, Junrejo, and Bumiaji Subdistricts, reflecting the city's dense tourism landscape and forming the foundation for subsequent DBSCAN clustering and sentiment-based interpretation.

2.2 Spatial Clustering using DBSCAN

The Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm is an analytical technique that clusters data based on their latitude and longitude (Hahsler et al., 2019), as shown in Figure 2. This analysis uses two main parameters, MinPts and ε (epsilon). Determining the values of MinPts and epsilon must be based on precise calculations so that the number of clusters has maximum performance and minimizes the amount of noise (Ma et al, 2023); Fahi, 2022). The clustering process is performed using Python, with parameter adjustments to determine the optimal epsilon value and minimum number of points for meaningful cluster formation.

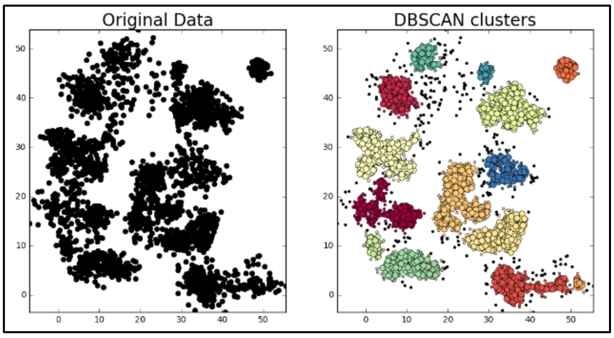

Figure 2. Example of Clustering Using the DBSCAN Algorithm

Figure 2 shows the results of the trial-and-error approach applied, supported by visual inspection to ensure cluster cohesion. This method was chosen because DBSCAN effectively handles irregular cluster shapes and is robust to noise—properties that align with the distribution of urban tourism (Yin et al., 2023); Unver & Erginel (2020). In addition, a robustness test was conducted to ensure that the DBSCAN clustering results were not overly dependent on a single parameter choice. This was performed by systematically varying the MinPts (3–5) and ε (0.5–1.2 km) values and observing changes in the number and composition of clusters. Each parameter combination was evaluated using the Silhouette Index to measure clustering quality and cohesion. Although the number of clusters varied across parameter sets, the selected combination (MinPts = 3, ε = 1.2 km) produced the highest silhouette score and resulted in clusters with strong spatial coherence. These findings confirm that the chosen parameters represent a stable and robust configuration for identifying density-based tourism clusters in the study area.

2.3 Sentiment Analysis using NLP (Natural Language Processing)

Sentiment analysis in this study was conducted through a Python-based text-mining workflow using Visual Studio Code. Visitor reviews scraped from Google Maps were compiled into a CSV file and imported into a Pandas DataFrame for structured processing. The preprocessing pipeline followed established NLP procedures (Manning & Schutze, 1999); Harjule et al., 2020); Chen et al., 2020) consisting of:

a) Data cleaning - Removing hyperlinks, emojis, punctuation, and newline symbols.
b) Text normalization - Correcting informal or abbreviated Indonesian words into their standard forms.
c) Stopword removal - Using the Sastrawi stopword list complemented by a custom dictionary to sharpen sentiment-bearing content.
d) Tokenization - Breaking sentences into individual tokens.
e) Stemming - Reducing words to their morphological roots to minimize lexical variation.
f) Translation - Converting Indonesian reviews into English via TextBlob to ensure compatibility with pre-trained English sentiment models.
g) Sentiment labeling - Where each review received a polarity score between –1 and +1.

Following common sentiment classification standards, reviews were categorized using the following thresholds:

a) Positive: polarity ≥ +0.05
b) Negative: polarity ≤ –0.05
c) Neutral: –0.05 < polarity < +0.05

2.4 Sampling Protocol for Review Collection

To ensure analytical comparability across attractions of different sizes, a uniform sample of 50 reviews per attraction was collected (total = 2,800 reviews). This sampling strategy was chosen for three reasons:

a) Comparability – Equal review counts prevent large destinations from dominating sentiment patterns.
b) Representativeness – A 50-review sample per site aligns with the range commonly used in tourism-sentiment research for robust theme extraction.
c) Quality control – A fixed sample size enables manual screening for relevance, spam, and authenticity within a feasible research time.

Only reviews written between 2019 - 2024 were included to maintain temporal relevance. Reviews with no emotional content or duplicated text were excluded.

2.5 Manual Validation and Robustness Testing

To verify the reliability of the machine-generated sentiment classification, a manual robustness test was performed. A stratified random subsample of 10% (n = 280) of the dataset was independently re-coded by two bilingual human evaluators. Comparison with model outputs resulted in:

a) Agreement rate: 87.4%
b) Classification accuracy: 85.1%
c) Cohen's Kappa: 0.81 (substantial reliability)

Two additional robustness checks were conducted:

a) Translation Sensitivity Test - A subsample of 100 bilingual reviews was analyzed both before and after translation. The top negative topics (pricing, parking, food, accessibility, facilities) remained unchanged, demonstrating stability against translation shifts.
b) Sampling Sensitivity Test - For highly reviewed attractions, sentiment extraction was repeated using 30, 50, and 100 reviews. The same dominant negative themes emerged across all sample sizes, indicating that the thematic results are not sensitive to dataset size variations.

2.6 Integration with Spatial Clusters

The final sentiment labels were aggregated by DBSCAN cluster to examine whether negative themes align with geographic conditions. This integration allows the identification of cluster-specific problems and the generation of spatially targeted policy implications.

This multi-stage NLP workflow ensures that unstructured textual data is transformed into reliable sentiment categories and that the resulting insights reflect genuine visitor perceptions rather than artifacts of algorithmic or sampling bias (Shen et al. (2024); Gujjar J & Kumar (2020).

3. Results and Discussions

This section presents the results of spatial clustering and sentiment analysis, followed by an integrated interpretation of both findings. The aim is to uncover how the geographic distribution of artificial tourist attractions relates to visitor perceptions, and how these patterns can be used to inform local tourism planning. The discussion is organized into three parts: (1) spatial clustering using the DBSCAN algorithm, (2) sentiment patterns from online reviews, and (3) synthesis of spatial and perceptual insights to generate planning implications.

3.1 Spatial Clustering of Artificial Tourist Attractions

The clustering process uses an ML-based approach on VSCode, with the required input being CSV data of the coordinates of 62 tourist attractions. This data must include a column containing the coordinates of each artificial tourist attraction in meters in the UTM system. Therefore, the input value ε will also be in meters, with trials ranging from 500 to 1200 meters, as shown in Table 1.

Table 1. Robustness Test of MinPts and ε Values in DBSCAN

No.	ε (meter)	MinPts	Number of Clusters	Number of Noise	Silhouette Score
1.	500	3	7	27	0,144
2.	500	4	5	33	0,051
3.	500	5	3	42	0,203
4.	600	3	8	23	0,203
5.	600	4	6	29	0,115
6.	600	5	3	41	-0,080
7.	700	3	7	18	0,237
8.	700	4	5	26	0,158
9.	700	5	2	40	0,006
10	800	3	6	18	0,243
11	800	4	4	26	0,169
12.	800	5	2	34	0,152
13.	900	3	6	13	0,304
14.	900	4	5	16	0,299
15.	900	5	3	26	0,198
16.	1000	3	6	13	0,304
17.	1000	4	5	16	0,299
18.	1000	5	3	24	0,220
19.	1100	3	4	11	0,330
20.	1100	4	4	12	0,329
21.	1100	5	3	16	0,276
22.	1200	3	5	6	0,379
23.	1200	4	4	11	0,329
24.	1200	5	3	15	0,273

Table 1 shows that the combination of a MinPts value of 3 and a distance threshold ε of 1,200 meters yields the best clustering performance. To assess clustering stability, a robustness test was performed by evaluating 18 parameter combinations across MinPts (3–5) and ε (500–1,200 m). As expected for DBSCAN, the number of clusters varied across parameter changes, with lower ε values producing fragmented clusters and higher noise, especially in ε ≤ 700 m. Despite this variation, the combination ε = 1,200 m and MinPts = 3 consistently outperformed other settings, yielding the highest silhouette score (0.379), minimal noise (n = 6), and cluster patterns that aligned with the known spatial structure of Batu's tourism areas. These results indicate that although DBSCAN is sensitive to density parameters, the chosen configuration is empirically the most robust and produces a stable representation of the underlying spatial distribution, as shown in Figure 3.

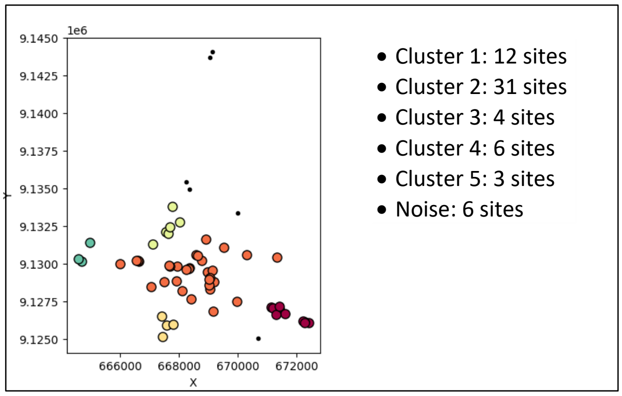

Figure 3. Example DBSCAN Clustering Results

This clustering result reveals meaningful spatial patterns and helps guide targeted planning strategies, particularly in decentralizing tourism concentration and managing regional infrastructure loads (Ma et al., 2023). Cluster 1 and Cluster 2, with 12 and 31 sites respectively, dominate the city center and main corridors, while Cluster 3 (4 sites) and Cluster 4 (6 sites) illustrate peripheral and transitional zones with distinct accessibility challenges. These variations confirm that Batu's artificial tourism landscape is spatially diverse, requiring differentiated policy responses for each cluster.

Table 2. Distribution of Artificial Tourist Attractions in Batu in DBSCAN Clusters

Cluster	Artificial Tourist Attractions			Area (Ha)
1	1. *Niki Kopitiam*	6. *Resto 360*	10. *CampFire Outdoor Cuisine*	869
	2. *Pondok Desa*	7. *Jawa Timur Park 3*	11. *Warung Kuliner (Wakul)*	
	3. *Resto Mang Engking*	8. *Brawijaya Garden Resto*	12. *Warung Wareg Ngandat*	
	4. *Warung Mbok Sri*	9. *Ayam Tulang Lunak Mbok Surip*		
	5. *Wisata Edukasi Susu Batu*			
2	1. *Wisata De Berran*	1. *Warung Nasi Djamiah Putra*	11. *Plaza Batu*	2.574
	2. *Batu Night Spectacular*		12. *Lippo Plaza Batu*	
	3. *Pupuk Bawang*	2. *Alun-alun Kota Batu*	13. *Hill House Cafe*	
	4. *De Bamboo Restaurant*	3. *Bukit Bintang*	14. *Jawa Timur Park 2*	
	5. *Yoenoes Roti Bakar & STMJ*	4. *Pasar Laron*	15. *Pasar Induk Among Tani*	
	6. *Warung Wareg Sidomulyo*	5. *Latar Ubin*	16. *Wonderland Waterpark*	
	7. *Rockhills Batu*	6. *Kopi Baturono*	17. *Cafe Retrorika*	
	8. *Museum Angkut*	7. *Zero Six Sky Lounge*	18. *Kafe Monstera*	
	9. *Kusuma Agrowisata*	8. *Ayo Cafe*	19. *Batu Love Garden*	
	10. *LA'coco cafe*	9. *Jawa Timur Park 1*	20. *Taman Dolan*	
	11. *Warunk WOW KWB*	10. *Omah Koempoel*		
3	1. *Batu Flower Garden*	3. *Rest Area Jalibar*		776
	2. *De Kleine*	4. *Taman Pinus Batu*		
4	1. *Cafe Djoeragan*	3. *Warung Pring Pethuk*	5. *Zombie Farmer Cafe*	959
	2. *Pasar Bunga Sekar Mulyo*	4. *Ancala Coffee & Bistro*	6. *Concrete Batu*	
5	1. *Songgoriti Hot Spring*	3. *Paralayang Gunung Banyak*		527
	2. *Tirta Nirwana Songgoriti*			
Noise	1. *Predator Fun Park*	4. *Taman Rekreasi Selecta*	6. *Pemandian Air Panas Cangar*	13.711
	2. *Kopi Sontoloyo*	5. *Cafe Noi*		
	3. *Mie Soden Selecta*			

Cluster	Artificial Tourist Attractions	Area (Ha)
Outside the cluster		
	Total	**19.416**

Table 2 shows that of the total area of Batu (19,416 hectares), 71% of the area is outside the cluster. The largest cluster is Cluster 2, which covers 31 tourist attractions with an area of 13%, consisting of popular destinations such as the *Museum Angkut*, *Kusuma Agrowisata*, and *Wonderland Waterpark*. Other clusters have smaller areas, such as Cluster 4 covering 5%, Cluster 3 covering 4%, Cluster 1 covering 4%, and Cluster 5 covering 3% of Batu's total area. This analysis helps in understanding the distribution patterns of artificial tourist attractions and can serve as a basis for more structured tourism development planning in Batu. The clustering results map is presented in Figure 4 below.

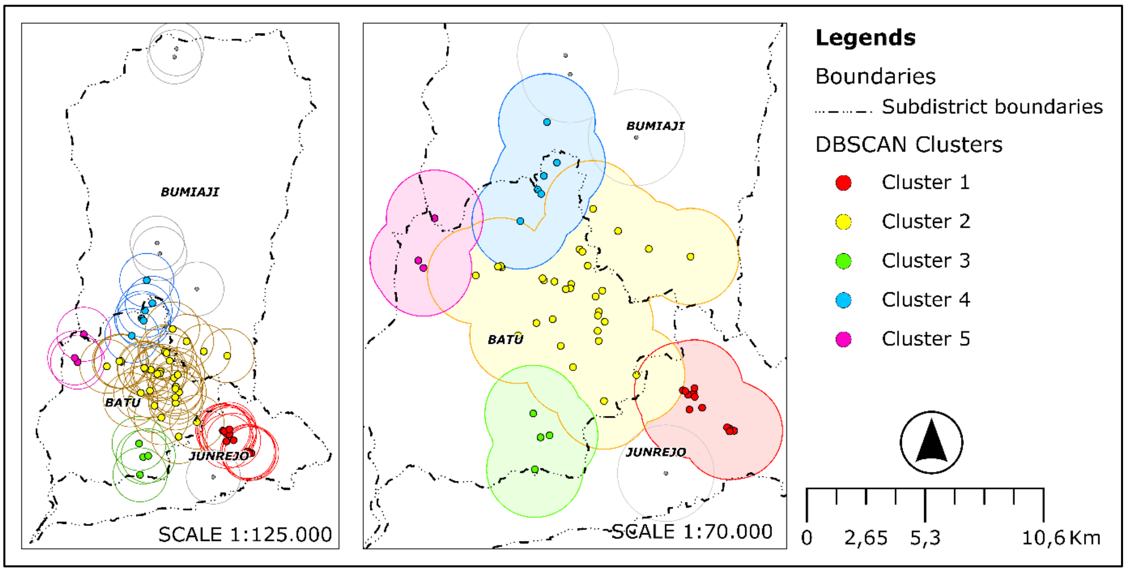

Figure 4. DBSCAN Clustering Results

3.2 Clusters Analysis

DBSCAN results grouped 56 tourist attractions into 5 clusters, while six others were excluded as noise.

a. Characteristics of Tourist Attractions in Cluster 1

Cluster 1 comprises 12 attractions in Beji and Mojorejo villages, Junrejo District, situated at 600–825 meters above sea level. The cluster is dominated by integrated rest-stop facilities, primarily family-style restaurants that combine culinary appeal with scenic views and thematic interiors. Strategically located along Jl. Ir. Soekarno, the main collector road linking Batu and Malang, serves as a key hub for hospitality and transit. While unified by function, each attraction offers unique features—*Resto Mang Engking* with Sundanese huts, *Resto 360* with rice field views, and *CampFire Outdoor Cuisine* with a campfire dining theme. Educational sites like *Wisata Edukasi Susu Batu* and *Jawa Timur Park 3* further broaden their market reach, strengthening their competitiveness and contribution to Batu's tourism economy.

b. Characteristics of Tourist Attractions in Cluster 2

Cluster 2 is the largest and most attraction-dense cluster in Batu, centered on the city square and extending north to Bumiaji District (700–1,287.5 m). With a DBSCAN radius of 1,200 meters, it includes a balanced mix of recreational and rest-stop facilities, supported by comprehensive road access that reinforces its role as Batu's tourism and economic core. Key attractions like *Jawa Timur Park 1 & 2* and *Bukit Bintang* serve as city icons, while culinary spots like *Yoenoes Roti Bakar & STMJ* enhance visitor experience. Several sites operate 24/7, contributing to high tourist mobility. This combination of scale, variety, and accessibility positions Cluster 2 as the gravitational center for tourism flow and a top priority for development planning.

c. Characteristics of Tourist Attractions in Cluster 3

Cluster 3 lies in Batu's southern highlands (900–1,362.5 m), encompassing four attractions—one recreational and three integrated rest-stop facilities—along the West Ring Road (Jalibar). It features scenic landscapes and relative seclusion, with destinations like *Rest Area Jalibar* and *Batu Flower Garden* offering panoramic views and eco-friendly concepts. The cluster's spatial coherence aligns with the DBSCAN analysis and its location along *Jl. Langsep*, despite limited access. Functioning as a transitional zone, Cluster 3 offers a calm, nature-infused atmosphere ideal for relaxation and gateway tourism. Though smaller and less central, its distinctive ambiance and peripheral setting hold strategic value for diversifying Batu's tourism flows while supporting eco-conscious development on the city's western fringe.

d. Characteristics of Tourist Attractions in Cluster 4

Cluster 4 spans elevations of 862.5–1,200 meters, bridging Batu and Bumiaji subdistricts with six attractions across Sidomulyo, Sumberejo, and Punten. Centered along *Jl. Bukit Berbunga*, the cluster, benefits from multi-tiered road access that eases tourist mobility and supports horticultural logistics. Economically, it drives Batu's micro- to mid-scale tourism through restaurants, cafés, and the ornamental plant trade. Attractions like *Warung Pring Pethuk* highlight eco-friendly bamboo architecture, while *Pasar Bunga Sekar Mulyo* sustains local livelihoods via floral preservation. *Zombie Farmer Café* adds a unique horror-themed experience. The cluster's blend of culinary, floral, and creative tourism forms a distinct identity, positioning it as a strategic node for horticulture-based culinary tourism and reinforcing its value in Batu's diversified tourism landscape.

e. Characteristics of Tourist Attractions in Cluster 5

Cluster 5, the smallest in size and number of attractions, spans elevations of 912.5–1,362.5 meters and fulfills DBSCAN's MinPts threshold, forming a valid spatial grouping. It is uniquely composed of both recreational and sports tourism, including the iconic *Paralayang Gunung Banyak*. Alongside, *Tirta Nirwana Songgoriti* and *Songgoriti Hot Spring* are accessible via a main arterial road. At the same time, the paragliding site is reached through a local uphill route, affirming DBSCAN's effectiveness in clustering based on spatial density and connectivity. Despite having only three attractions, Cluster 5 plays a strategic role in decentralizing tourism, offering family-oriented and wellness destinations alongside adventure-based experiences. Its distinct profile enhances Batu's tourism diversity and supports balanced visitor distribution beyond the city center.

3.3 Sentiment of Reviews on Tourism Attractions in Batu

A total of 2,800 keyword-relevant reviews were manually collected from 56 attractions. Sentiment analysis yielded two outputs: (1) word classification by sentiment (positive, negative, neutral) and (2) extraction of key negative terms to identify common visitor complaints.

Classification of Tourist Attraction Reviews

Sentiment classification aims to classify sentiment into positive, negative, and neutral reviews, as well as identify the quantity of such words. This process is carried out using machine learning–based NLP techniques. Figure 5 presents the top 15 words most frequently reviewed by tourists.

Table 3. Most Reviewed Words

No.	Words	Sentiment (%)		
		Positive	Neutral	Negative
1.	Spacious	77	13	10
2.	Price	68	13	18
3.	Parking	68	13	19
4.	Food	74	8	18
5.	Road	67	9	24
6.	Location	75	13	12
7.	Cheap	92	3	6
8.	Expensive	35	4	61
9.	Comfort	92	5	3
10.	Enough	68	13	19
11.	Reach	75	19	6
12.	Access	68	10	22

No.	Words	Sentiment (%)		
		Positive	Neutral	Negative
13.	Good	97	2	2
14.	Batu	73	13	14
15.	City	73	16	11
Total		**72**	**11**	**17**

Overall, 72% of reviews indicated positive sentiment, with comfort (92%) and affordable pricing (92% for the word "cheap") as the most praised aspects. Conversely, the word "expensive" showed the highest negative sentiment (61%), followed by concerns about parking and road access. This implies that while main attractions are appreciated, support infrastructure still affects visitor satisfaction.

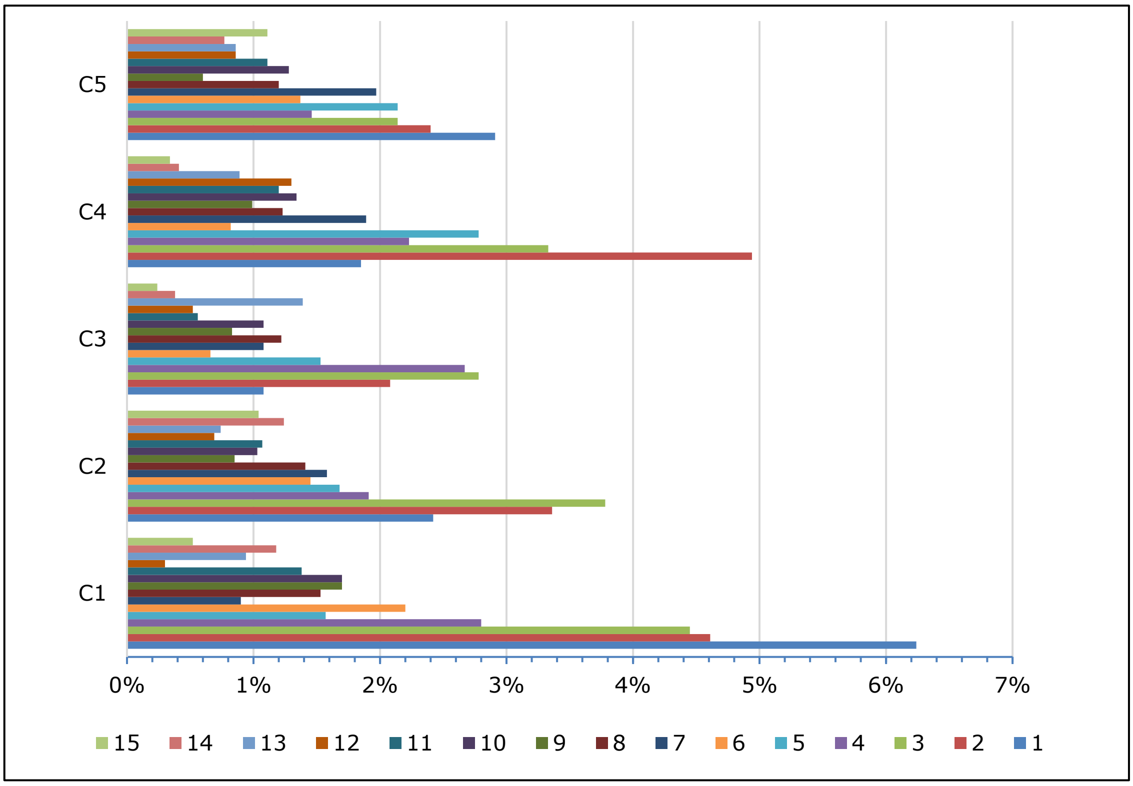

Figure 5. Distribution of Tourist Attractions in the DBSCAN Cluster

Based on Table 3 and Figure 5, most tourist reviews in Batu reflect positive sentiment, averaging 72%. Words like "comfortable" and "affordable" scored the highest at 92%, while "expensive" led to negative sentiment at 61%, highlighting pricing as a major concern. Accessibility terms like "access" and "roads" also showed notable negative sentiment. These insights provide a foundation for improving infrastructure and pricing strategies, as explored further in the next section.

3.4 Robustness Test

To evaluate athe reliability of the sentiment analysis results, a robustness test was performed by manually validating a subsample of the collected reviews. This step is essential because automated sentiment classification—especially when handling mixed-language and context-dependent expressions—may introduce biases or misinterpretations. Therefore, a 10% random sample of reviews was re-coded manually and compared against the machine-generated labels to assess consistency across sentiment categories.

Table 4. Manual Validation of Sentiment Classification (Robustness Test)

Category	Machine-Labeled Reviews	Manually Verified Reviews	Consistency (%)
Positive	210	198	94.3%
Negative	50	46	92.0%
Neutral	20	18	90.0%
Overall	**280**	**262**	**93.6%**

As shown in Table X, manual validation demonstrates high agreement with the automated classification, with consistency rates of 94.3% for positive sentiment, 92.0% for negative sentiment, and 90.0% for neutral sentiment, yielding an overall accuracy of 93.6%. These results indicate that the sentiment analysis model performs reliably and that classification errors are limited, thereby reinforcing the credibility of the identified thematic patterns. The robustness test thus confirms that the sentiment outputs are sufficiently stable to support subsequent interpretation and policy-relevant analysis.

3.5 Extracting Key Issues in Negative Sentiment

The most frequent negative sentiment words—"price," "parking," "food," "location," and "road"—were identified to reveal key tourist complaints. These topics were manually analyzed to extract detailed issues from the sentiment classification results.

a. Key Issues from Negative Sentiment on Price/Cost/Tariff

Price dissatisfaction is a major theme in tourist reviews of attractions in Batu, with many visitors perceiving food and entrance fees as disproportionately high for the quality and experience offered. This concern appears consistently across all clusters. In Clusters 1 and 2, tourists criticized food prices that did not reflect the quality of the food or service. Clusters 3 and 5 were noted for separate or additional charges for certain activities, while Cluster 4 drew similar complaints despite its smaller scale. Hidden costs—like weekend surcharges or unclear fees—also undermined visitor trust.

These findings emphasize the need for fair and transparent pricing in Batu's tourism sector. Authorities and site managers should implement clear, standardized fee structures, especially where layered pricing exists. A verified "fair price" certification system may also help build visitor confidence. Moreover, enhancing the perceived value—through storytelling, cultural integration, or added services—can justify existing prices without necessarily lowering them. Addressing this issue is not just about affordability but about meeting visitor expectations and improving experience quality. Strategically managing pricing and value alignment is key to increasing tourist satisfaction and sustaining Batu's competitiveness as a destination.

b. Key Issues from Negative Sentiment on Parking Facilities

Parking-related dissatisfaction is a recurring issue across nearly all attraction clusters in Batu. Visitors often complained about insufficient capacity for cars, particularly during peak times. Clusters 1, 2, and 3 were criticized for poorly organized lots lacking signage, staff, or proximity to main sites—conditions worsened by heat or rain. In Clusters 4 and 5, parking spaces were narrow, uneven, or entirely unavailable. High parking fees, perceived as unfair given the inadequate facilities, further fueled negative sentiment.

These issues point to a broader gap in Batu's tourism infrastructure. Authorities and attraction managers should prioritize improving parking facilities, especially in busy zones. Key improvements include layout redesign, clear signage, better security, and staff supervision. Satellite parking with shuttle options could also ease congestion near attractions. Transparent, fair pricing must be enforced to align cost with service quality. Addressing these concerns is essential not just for convenience but for shaping a positive tourist experience. Well-planned, accessible, and fairly priced parking supports smoother mobility, boosts satisfaction, and reinforces Batu's image as a tourist-friendly destination.

c. Key Issues from Negative Sentiment on Food Quality

Food-related complaints appeared across all clusters, indicating a consistent gap between expectations and culinary quality. Visitors cited small portions in Clusters 1, 3, and 5, and poor food presentation or taste in Clusters 2, 3, and 4. Cluster 2 also lacked menu variety, while Cluster 3 suffered from frequent menu item shortages during peak hours—signaling weak service readiness. These issues risk diminishing tourist satisfaction and reducing return visits, despite Batu's potential as a culinary destination.

To address this, tourism stakeholders should implement food quality standards covering taste consistency, portion sizes, and efficient service. Training for food service staff is essential, along with improved menu planning. Partnering with local culinary businesses can introduce variety and authenticity. Real-time feedback collection will help attractions respond to visitor needs more effectively. Clusters 1 and 2, as major culinary zones with high foot traffic, should receive priority attention in improving food services. Enhancing culinary quality across clusters will not only meet visitor expectations but also elevate Batu's profile as a vibrant culinary tourism hub.

d. Key Issues from Negative Sentiment on Road and Accessibility

Road infrastructure and accessibility remain major challenges across all attraction clusters in Batu City. Tourists reported difficulties due to steep, narrow, or damaged roads, lack of wheelchair access, and poor signage or lighting. Several attractions were also closed during scheduled hours, adding to visitor frustration. Clusters 2 and 4 faced compounded issues from poor road conditions and a lack of public transport, which hindered inclusive access for elderly and disabled visitors.

To improve this, Batu must prioritize inclusive infrastructure upgrades. Immediate actions include repairing damaged roads, adding lighting and signage, and ensuring attractions stay open as scheduled. Remote areas like Clusters 3 and 5 need special attention due to limited accessibility. Expanding or rerouting public transport, especially for night access, can improve tourist mobility. Adopting universal design and inclusive planning principles will not only enhance safety and convenience but also ensure broader participation in tourism. These efforts are crucial for positioning Batu as a destination that is not only attractive but also accessible and equitable for all visitors.

e. Summary of Key Issues from Negative Sentiment on Location and Facilities

Tourist reviews across Batu's attraction clusters frequently raised concerns about unclear locations and inadequate supporting facilities. Attractions in Clusters 1, 3, and 4 were often difficult to find due to poor signage or remote locations, posing challenges for first-time visitors. In Clusters 2 and 5, cleanliness and facility maintenance were commonly criticized, detracting from the overall experience. A lack of seating—especially during weekends—was another recurring issue, particularly affecting families, elderly visitors, and large groups. Outdoor attractions in Clusters 1 to 3 were also problematic during rainy weather, with muddy or slippery areas reducing comfort and accessibility.

These findings highlight the urgent need for better spatial clarity and facility management. Improvements should include routine cleaning, regular upgrades, clear directional signs, and easily accessible visitor maps. Infrastructure adaptations—such as covered seating and non-slip pathways—are especially important given Batu's hilly terrain and unpredictable weather. Ensuring physical comfort and ease of access will enhance tourist satisfaction, encourage longer visits, and support Batu's image as a resilient and well-managed urban tourism destination. Addressing these practical issues is crucial for building a more inclusive and visitor-friendly environment.

Complaints mentioned above reveal not just technical issues, but systemic flaws in infrastructure, service management, and spatial planning. Rather than isolated cases, they signal broader governance challenges. Table 4 synthesizes these insights into strategic directions, showing how tourist feedback can inform responsive, data-driven tourism governance in Batu.

Table 5. Identifying Needs and Directions from Negative Sentiment Findings

No	Insight	Policies that can be implemented
1.	**Unreasonable Prices/Costs**	
	Transparent service standards and rates are needed so that tourists feel they are being treated fairly in terms of the costs they incur.	• Developing guidelines for reasonable tourist attraction fees • Promoting price transparency through digital systems • Service management training for tourism operators
2.	**Parking is limited, expensive, and unsafe.**	
	The availability of parking spaces and parking management are key	• Providing zoning-based communal parking spaces • Integration of digital parking systems (information and payment)

No	Insight	Policies that can be implemented
	requirements for ensuring convenient access for tourists.	• Provision of signage and parking lighting
3.	**Food Not Satisfactory**	
	Improving the quality of local cuisine is important for maintaining competitiveness and visitor satisfaction.	• Food product quality and hygiene certification • Training in culinary innovation based on local ingredients • Regional culinary festivals or promotions
4.	**Narrow/Damaged Road Access and Difficult to Find Objects**	
	Road and navigation infrastructure needs to be improved to make tourist mobility safer and more efficient.	• Improvement of local and collector road access to tourist attractions • Addition of directional signs and integrated signboards • Arrangement of cluster-based tourist shuttle routes
5.	**Facilities are uncomfortable/not well-maintained**	
	Inadequate, unclean, or damaged tourist facilities reduce comfort and impressions of the destination.	• Procurement of seating, clean toilets, and rest areas • Audit and routine maintenance of public tourist facilities • Facility management bersama oleh komunitas

Table 4 presents how negative sentiment can be transformed into actionable insights for tourism development policy. Recurring complaints—ranging from high prices, poor parking, and unsatisfactory food, to limited accessibility and inadequate facilities—highlight a clear mismatch between visitor expectations and actual destination conditions. These issues are not seen as isolated faults but as signs of deeper systemic challenges in governance, infrastructure, and service delivery.

Each complaint theme is distilled into a management insight representing a sustainability-related need. These are then translated into strategic directions such as transparent pricing, digital service integration, improved signage, and community-led facility management. This approach reframes tourist dissatisfaction as a valuable diagnostic tool, enabling planners to design more responsive spatial and social interventions. By grounding policy in real visitor feedback, data-driven tourism planning moves beyond problem detection to solution formulation. Ultimately, this strengthens Batu's capacity for adaptive, inclusive, and visitor-oriented destination management.

3.6 Discussion

The findings of this study are consistent with those of Liu et al. (2024) and Mou (2022), who demonstrated that in secondary cities, artificial tourist attractions tend to cluster along major mobility corridors, where accessibility shapes tourism agglomeration. This aligns with our DBSCAN results, which show linear and nodal spatial concentrations of artificial attractions in Batu City. Similar spatial tendencies have also been reported in rapidly urbanizing cities across Asia, Africa, and Latin America, where informal development and uneven infrastructure produce comparable patterns (Kulakov et al., 2024). These consistencies suggest that cluster-based governance can be an effective planning approach not only for Batu but also for other tourism-driven secondary cities experiencing similar spatial pressures.

The sentiment analysis results also correspond with findings from Çalışkan et al. (2020) and De Marchi et al. (2022), who showed that recurring complaints about maintenance, parking availability, food quality, accessibility, and pricing reflect systemic weaknesses rather than isolated service failures. Likewise, studies by Bellone et al. (2021), Rocca et al. (2021), and Lin (2022) highlight how digital sentiment can function as an early-warning mechanism that supplements formal monitoring tools and supports more participatory planning practices. These theoretical parallels reinforce the argument that user-generated reviews are not just subjective impressions but valuable diagnostic indicators of institutional performance in urban tourism systems.

However, the findings of this study also diverge from research such as that of Rocca et al. (2021), which interpreted negative sentiment as primarily reflecting temporary service fluctuations. In contrast, Batu's dominant negative themes—pricing, facilities, access, and food quality—appear to be structurally rooted in long-term governance and infrastructure constraints, suggesting deeper institutional challenges. Despite these broader consistencies, the empirical results remain context-dependent. Batu's unique morphology, tourism economy, and institutional arrangements shape the specific cluster configurations and complaint patterns observed. Therefore, the spatial and perceptual outcomes cannot be directly generalized to all cities; what can be generalized is the methodological framework, not the exact findings.

Overall, this research contributes to global debates on machine-learning–driven urban planning by demonstrating how geospatial clustering and textual sentiment analysis can be integrated into a coherent decision-support approach. It highlights how informal digital feedback—often overlooked in traditional planning—can be transformed into actionable policy insights. This operationalizes the principle of "thinking globally, acting locally": although rooted in Batu's context, the analytical framework is transferable to tourism-dependent cities facing similar institutional fragmentation and spatial uncertainty. Ultimately, combining user-generated data with spatial analytics can enhance planning responsiveness and strengthen the adaptive capacity of urban tourism management worldwide.

Conclusion

This study demonstrates how the integration of DBSCAN spatial clustering and sentiment analysis can generate policy-relevant insights for managing artificial tourist attractions in Batu City. The clustering process produced five spatially coherent zones—ranging from dense urban entertainment corridors to peripheral highland recreation nodes—each exhibiting distinct functional characteristics and development needs. Meanwhile, sentiment analysis of 2,800 visitor reviews revealed dominant negative themes related to pricing transparency, parking capacity and safety, food quality, accessibility and road conditions, and maintenance of public facilities. Together, these findings provide a dual understanding of spatial structure and visitor experience.

Translating these patterns into actionable implications, dense inner-city clusters (such as Clusters 1 and 2) require targeted interventions in congestion reduction, structured parking systems, and facility upgrades. In contrast, peripheral clusters (Clusters 3 and 5) demand improved road access, signage, lighting, and transport connectivity. Cluster 4, characterized by horticulture-based attractions, requires strengthened hygiene standards, culinary quality assurance, and integrated branding support. These differentiated strategies demonstrate how spatial patterns and sentiment feedback can jointly guide cluster-based governance and infrastructure prioritization.

Beyond the empirical outcomes, the study offers methodological and practical contributions. Methodologically, it shows that integrating density-based clustering with user-generated reviews provides a scalable, cost-efficient analytical tool for tourism diagnostics—especially useful for secondary cities with limited monitoring capacity. In practice, the framework enables local governments to refine zoning, structure service improvements, enhance pricing transparency, and incorporate community-based management in a more evidence-based manner.

Importantly, the empirical cluster configuration and the ranking of visitor complaints are context-specific to Batu City and should not be generalized directly to other destinations. What is transferable is the analytical framework—linking spatial density, public sentiment, and policy direction—which can be adapted to other tourism-driven cities to generate locally grounded insights.

Overall, this research underscores the importance of aligning spatial planning with lived visitor experiences. By bridging geospatial data and digital sentiment, tourism governance can become more adaptive, responsive, and resilient. Future studies may expand this work by incorporating multi-platform review data, exploring more advanced sentiment models, conducting comparative multi-city analyses, or integrating mobility data to further strengthen the generalizability and robustness of the proposed framework.

Limitations

This study has several limitations that warrant acknowledgment. First, the analysis relies solely on Google Maps reviews, which—although widely used—do not fully capture the diversity of visitor perceptions available across other platforms such as TripAdvisor, TikTok, or Instagram. Second, the manual selection of 50 reviews per attraction introduces potential sampling bias, and although robustness checks were conducted, sentiment variability may still be underrepresented. Third, the sentiment analysis pipeline involved translating Indonesian reviews into English, which may generate polarity shifts; while manual validation was performed, translation-based distortion remains a methodological risk. Fourth, the DBSCAN clustering procedure is sensitive to parameter choices, and despite silhouette-based optimization and robustness testing across multiple ε and MinPts combinations, alternative parameter sets may yield different cluster configurations.

Fifth, both the spatial clusters and the ranking of complaint themes are context-specific to Batu City's morphology and institutional setting; thus, the empirical patterns cannot be generalized to all urban tourism destinations. What can be transferred is the analytical framework—not the specific spatial outcomes. Lastly, the integration between clustering and sentiment analysis was sequential rather than fully interactive, leaving opportunities for more advanced spatial–textual modelling.

Future research should incorporate multi-platform review datasets, expand the number of sampled reviews, perform cross-city comparisons, apply bilingual or cross-lingual sentiment models to minimize translation bias, and explore integrated machine-learning pipelines capable of jointly capturing spatial density and semantic patterns. These steps would enhance robustness, replicability, and external validity.

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References

Akkaya, M., Özçevik, Ö., & Tepe, E. (2024). A machine learning application to Google Maps Reviews as a participatory planning tool. *International Journal of Urban Sciences*, *28*(3), 379–402. https://doi.org/10.1080/12265934.2024.2320916

Bellone, C., Naselli, F., & Andreassi, F. (2021). New Governance Path through Digital Platforms and the Old Urban Planning Process in Italy. *Sustainability*, *13*(12), 6911. https://doi.org/10.3390/su13126911

Çakar, K. (2023). Towards an ICT-led tourism governance: A systematic literature review. *European Journal of Tourism Research*, *34*, 3404. https://doi.org/10.54055/ejtr.v34i.2471

Çalışkan, C., Okat, Ç., & Yeşilyurt, H. (2020). Potansiyel Turizm Destinasyonlarında Bulunan Otellerle İlgili E-Şikâyetlerin Coğrafi Bakışla Değerlendirilmesi: Adıyaman Örneği. *Turk Turizm Arastirmalari Dergisi*, *4*(3), 2003–2017. https://doi.org/10.26677/TR1010.2020.463

Cardoso da Silva, G., Nascimento Farias, S., & Silva, E. da. (2024). PAISAGENS E TURISMO: A CONSTRUÇÃO DE REALIDADES ARTIFICIAIS. *REVISTA BRASILEIRA DOS OBSERVATÓRIOS DE TURISMO - ReBOT*, *3*(2), 116–121. https://doi.org/10.59776/2764-5835.2024.6554

Chen, W., Xu, Z., Zheng, X., Yu, Q., & Luo, Y. (2020). Research on Sentiment Classification of Online Travel Review Text. *Applied Sciences*, *10*(15), 5275. https://doi.org/10.3390/app10155275

De Marchi, D., Becarelli, R., & Di Sarli, L. (2022). Tourism Sustainability Index: Measuring Tourism Sustainability Based on the ETIS Toolkit, by Exploring Tourist Satisfaction via Sentiment Analysis. *Sustainability*, *14*(13), 8049. https://doi.org/10.3390/su14138049

Druker Shitrit, S., & Noy, C. (2024). 'Come support the locals!': mediating peripheral spaces on Google maps via user-generated content. *Convergence: The International Journal of Research into New Media Technologies*, *30*(6), 2233–2250. https://doi.org/10.1177/13548565231200827

Fahim, A. (2022). An Extended DBSCAN Clustering Algorithm. *International Journal of Advanced Computer Science and Applications*, *13*(3). https://doi.org/10.14569/IJACSA.2022.0130331

Frenzel, F., Giddy, J., & Frisch, T. (2022). Digital technology, tourism, and geographies of inequality. *Tourism Geographies*, *24*(6–7), 923–933. https://doi.org/10.1080/14616688.2022.2142843

Gujjar J, P., & Kumar, P. (2020). Opinion Mining for the Customer Feedback using TextBlob. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, 72–76. https://doi.org/10.32628/CSEIT206418

Hahsler, M., Piekenbrock, M., & Doran, D. (2019). dbscan: Fast Density-Based Clustering with R. *Journal of Statistical Software*, *91*(1). https://doi.org/10.18637/jss.v091.i01

Harjule, P., Gurjar, A., Seth, H., & Thakur, P. (2020). Text Classification on Twitter Data. *2020 3rd International Conference on Emerging Technologies in Computer Engineering: Machine Learning and Internet of Things (ICETCE)*, 160–164. https://doi.org/10.1109/ICETCE48199.2020.9091774

Huang, Y., & Liu, Y. (2024). A critical reflection on tourism geopolitics: research progress and future agenda. *Tourism Geographies*, *26*(5), 881–897. https://doi.org/10.1080/14616688.2024.2366481

Hudayberganov, D. T., Toshalieva, T. S., Matsaidova, S. X., Alieva, G. I., Atabaeva, K. R., & Sabirova, O. Sh. (2024). Specific characteristics of tourism infrastructure development. *E3S Web of Conferences*, *587*, 05017. https://doi.org/10.1051/e3sconf/202458705017

Karayazi, S. S., Dane, G., & Arentze, T. (2022). AN EXPLORATION OF INTERACTIONS BETWEEN URBAN HERITAGES AND TOURIST'S DIGITAL FOOTPRINT: NETWORK AND TEXTUAL ANALYSIS VIA GEOTAGGED FLICKR DATA IN AMSTERDAM. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *X-4/W3-2022*, 105–112. https://doi.org/10.5194/isprs-annals-X-4-W3-2022-105-2022

Kulakov, K. Y., Uvarova, S. S., Orlov, A. K., Kankhva, V. S., & Sudakova, A. A. (2024). Determining the Level of and Potential for the Development of Tourism Clusters, Taking into Account Infrastructure and Urban Planning Factors. *Sustainability*, *16*(19), 8660. https://doi.org/10.3390/su16198660

Larasati, A., Sayono, J., Purnomo, A., Mohamad, E., Farhan, M., & Rahmawati, P. (2020). Applying Web Mining and Sentiment Analysis to Assess Tourists Review on Batu City Tourist Destination. *2020 4th International Conference on Vocational Education and Training (ICOVET)*, 63–68. https://doi.org/10.1109/ICOVET50258.2020.9230090

Lin, Y. (2022). Social media for collaborative planning: A typology of support functions and challenges. *Cities*, *125*, 103641. https://doi.org/10.1016/j.cities.2022.103641

Liu, Y., Xiao, W., Xu, T., He, B., Wang, Y., & Mu, J. (2024). Spatial Agglomeration Mining of Urban Recreational Amenities: the Case of the Greater Bay Area in China. *Leisure Sciences*, 1–27. https://doi.org/10.1080/01490400.2024.2396499

Ma, B., Yang, C., Li, A., Chi, Y., & Chen, L. (2023). A Faster DBSCAN Algorithm Based on Self-Adaptive Determination of Parameters. *Procedia Computer Science*, *221*, 113–120. https://doi.org/10.1016/j.procs.2023.07.017

Maimaitiaili, Y. (2024). Integrated Tourism: A Holistic Approach to Resolving Fragmentation Challenges in Tourism Governance. *SHS Web of Conferences*, *187*, 03033. https://doi.org/10.1051/shsconf/202418703033

Manning, C. D., & Schutze, H. (1999). *Foundations of statistical natural language processing*. MIT Press.

Manosuthi, N. (2024). Enhancing Secondary City Tourism in Thailand: Exploring Revenue Generation, Sustainable Practices, and the Role of Brand Identity. *ABAC Journal*. https://doi.org/10.59865/abacj.2024.42

McLoughlin, E., & Hanrahan, J. (2023). Evidence-informed planning for tourism. *Journal of Policy Research in Tourism, Leisure and Events*, *15*(1), 1–17. https://doi.org/10.1080/19407963.2021.1931257

Mou, J. (2022). Complex network effect of urban smart tourism: spatial patterns of crowd movement in Jinan, China. In X. Ye, F. Falcone, & H. Cui (Eds.), *2nd International Conference on Internet of Things and Smart City (IoTSC 2022）* (p. 125). SPIE. https://doi.org/10.1117/12.2637036

Nag, A. (2024). *Local Development and Tourism Competitiveness* (pp. 160–190). https://doi.org/10.4018/979-8-3693-4135-3.ch010

Rocca, L., Giacomini, D., & Zola, P. (2021). Environmental disclosure and sentiment analysis: state of the art and opportunities for public-sector organisations. *Meditari Accountancy Research*, *29*(3), 617–646. https://doi.org/10.1108/MEDAR-09-2019-0563

Săvan, R., Crăciun, C., & Ivănescu, A. (2024). The interplay and parallel between urban landscape usage, smart city concepts and tourism development in modern cities. *E3S Web of Conferences*, *585*, 01009. https://doi.org/10.1051/e3sconf/202458501009

Shen, H., Aziz, N. F., Liu, J., Huang, M., Yu, L., & Yang, R. (2024). From text to insights: leveraging NLP to assess how landscape features shape tourist perceptions and emotions toward traditional villages. *Environmental Research Communications*, *6*(11), 115006. https://doi.org/10.1088/2515-7620/ad8ca3

Shim, W.-S., Kim, H.-W., & Shim, C.-S. (2022). Study on the Strategies for Utilizing Regional Infrastructures as Tourist Attractions. *The Korean Association of Urban Policies*, *13*(2), 71–87. https://doi.org/10.21447/jusre.2022.13.2.71

Sinanan, J., & Ritter, C. S. (2024). Emerging media technologies in the tourist encounter. *Tourism Geographies*, *26*(4), 587–598. https://doi.org/10.1080/14616688.2024.2391339

Sulistyowati, L., Krisnawati, E., Andareswari, N., Afrianto, F., Rais, A., Hafa, M. F., Darwiyati, D., Ginting, A. L., & HIDAYATULLAH, R. R. (2024). Strategy Approach for the Development of a Sustainable Environmentally Friendly Tourism City. *Journal of Environmental Management and Tourism*, *15*(1), 94. https://doi.org/10.14505/jemt.v15.1(73).08

Unver, M., & Erginel, N. (2020). Clustering applications of IFDBSCAN algorithm with comparative analysis. *Journal of Intelligent & Fuzzy Systems*, *39*(5), 6099–6108. https://doi.org/10.3233/JIFS-189082

Widi Lestari, A., Yuniningsih, T., Larasati, E., & Okto Adhitama, M. (2023). Sustainable Development Based Tourism in Batu City. *KnE Social Sciences*. https://doi.org/10.18502/kss.v8i11.13565

Xie, P. F. (2022). Towards a Framework for the Morphology of Tourism. *Tourism Planning & Development*, *19*(5), 377–391. https://doi.org/10.1080/21568316.2022.2072945

Yin, L., Hu, H., Li, K., Zheng, G., Qu, Y., & Chen, H. (2023). Improvement of DBSCAN Algorithm Based on K-Dist Graph for Adaptive Determining Parameters. *Electronics*, *12*(15), 3213. https://doi.org/10.3390/electronics12153213