Proceeding International Conference on Religion, Science and Education (2026) **5**, 1497-1504

Analyzing Digital Reputation and Business Sustainability of Restaurant in Makassar Based on Online Reviews Using K-Means Clustering

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Abstract: This study explores the interplay between digital reputation and business sustainability among restaurants in Makassar, Indonesia, utilizing secondary data retrieved from TripAdvisor (n = 271). The dataset captures two principal facets of online reputation—customer ratings and review counts—which together reflect consumer perception and engagement within the digital marketplace. Clustering analysis was performed using the K-Means algorithm, an unsupervised learning method for partitioning data. To determine the optimal number of clusters, multiple evaluation metrics were applied, including the Elbow Method, Silhouette Score, Davies–Bouldin Index (DBI), and Calinski–Harabasz Index (CHI). Although k = 2 yielded the most statistically efficient configuration, a four-cluster model (k = 4) was chosen for its enhanced interpretability and managerial relevance. The four resulting segments—Star Performers, Hidden Gems, Mass Popular, and Low Performers—offer a nuanced representation of digital reputation strategies within Makassar's culinary ecosystem. The findings reveal that highly rated restaurants with significant online engagement tend to exhibit stronger indicators of business resilience and customer trust. Beyond empirical segmentation, this study highlights the growing significance of digital ethics, data transparency, and responsible analytics as critical enablers of sustainable digital transformation. Overall, the research underscores the strategic role of data science in shaping ethical, inclusive, and sustainable business practices in the hospitality industry.

Keywords: Digital ethics, digital reputation, K-Means clustering, online reviews, sustainability.

Introduction

The culinary industry in Indonesia has experienced rapid growth over the past decade, in line with the increasing number of digital consumers. The Ministry of Tourism and Creative Economy (Kemenparekraf, 2023) reports that the culinary subsector contributes the largest share to the national creative economy. As consumer behavior becomes increasingly digital, online reviews have become a primary reference for consumers when making purchase decisions, especially for high-risk products and services such as restaurants and hotels (Filieri, 2016). Platforms such as TripAdvisor, Google Reviews, and Zomato allow consumers to evaluate service quality, taste, and restaurant ambiance through open rating and comment systems. There is a strong positive alignment between electronic Word of Mouth (e-WOM) feedback and the report's rankings, consistently high online reviews also maintain stable reputations over time despite limitations related to review volume and credibility (Asenova et al., 2024).

Digital reputation, especially as reflected in online reviews and electronic word-of-mouth (e-WOM), has become a crucial intangible asset for the long-term sustainability of restaurant businesses. Strong and consistently positive reviews on digital platforms help restaurants build customer trust, attract new patrons, and nurture repeat visits, thereby stabilizing revenue streams over time. Positive and negative reviews, trust,

ISSN 2829-3355 | EISSN 2828-8467

food and service quality, and source credibility significantly shape e-WOM in the restaurant sector, and that managers can use this information to better align offerings with customer expectations and maintain ongoing relationships (Fakir and Miah, 2022). Complementing this, Sharma and Pokharel (2024) find that the volume and quality of online restaurant reviews substantially influence consumers' propensity to visit, emphasizing that effective management of online ratings and narratives enhances visibility, perceived reliability, and ultimately business performance. Together, these studies indicate that cultivating a positive digital reputation is not only a short-term marketing tool but also a strategic driver of customer loyalty and financial resilience, supporting the overall sustainability of restaurant enterprises.

The growing volume of online review data demands structured analytical approaches to uncover meaningful patterns in how consumers evaluate restaurants. One widely used technique is K-Means clustering, an unsupervised method that groups observations based on similarity in rating attributes. Recent work by Ahmad, Yolanda, and Rismawan (2024) applied K-Means to TripAdvisor-style rating metrics, such as food, service, value, atmosphere, and overall satisfaction to segment 35811 restaurants across Indonesia and successfully identify distinct market segments based on customers online evaluations. This application aligns with broader evidence from segmentation research, where K-Means remains the most frequently used approach for clustering customer data because of its effectiveness in identifying behavioral and rating-based patterns across large datasets (Gomes & Meisen, 2023). Through this approach, online review datasets can be transformed into actionable insights that help managers and stakeholders better understand reputation structures and consumer perception dynamics in the restaurant industry.

Makassar City stands out as a promising study area because it is widely recognized as a major culinary-tourism hub in eastern Indonesia, with a rich tradition of local specialties and active promotion of its gastronomic heritage (Jariyah et al, 2024). However, despite this recognized culinary potential, empirical studies that systematically utilize online review data to analyze restaurant reputation in Makassar remain extremely limited. Most existing research on Indonesian hospitality review analytics focuses on hotel sectors or more heavily touristed regions, using text-mining and sentiment analysis methods to glean consumer feedback from platforms such as TripAdvisor and Agoda (Erniyati et al., 2023). Therefore, applying review-based clustering and data-driven segmentation to Makassar restaurants would fill a notable research gap by extending digital-review analysis into understudied yet culturally and economically significant regional culinary contexts.

Building on the importance of digital reputation and its role in sustaining competitiveness in the restaurant industry, this study aims to segment restaurants in Makassar using K-Means clustering based on rating scores and review counts derived from online customer feedback. To ensure meaningful and reliable segmentation, the optimal number of clusters is identified using established validation measures such as the Elbow Method, Silhouette Score, Davies–Bouldin Index, and Calinski–Harabasz Index (Salsabila & Leni, 2025). These analytical steps enable a clearer understanding of how digital reputation is distributed across different types of restaurants and how consumer perceptions form distinct reputation profiles within the city. From an academic perspective, the study enriches the limited body of research on data-driven digital reputation analysis in regional Indonesian culinary destinations. From a practical standpoint, the resulting segmentation offers valuable insights for restaurant operators and local policymakers in designing strategies that enhance customer engagement, strengthen brand credibility, and support long-term business sustainability. By interpreting online reviews through a structured clustering framework, this research not only categorizes restaurants statistically but also highlights the strategic significance of maintaining a strong and consistent digital reputation in a competitive culinary landscape.

Materials And Methods

This study utilized secondary data obtained from the TripAdvisor platform, covering 271 restaurants operating in the city of Makassar, Indonesia. The selection of TripAdvisor was based on its credibility as one of the most popular and most frequently visited platforms by travelers when making decisions related to accommodations and travel (Sayfuddin & Chen., 2021). Data were collected automatically using web scraping techniques, employing Python libraries such as requests-html and BeautifulSoup, which enabled the extraction of structured information without manual intervention.

Research Variables

The main variables analyzed in this study consist of two quantitative indicators: rating and review count. The rating represents the overall score assigned by TripAdvisor users on a 1-5 scale, reflecting consumers perceived quality of a restaurant's offerings. Meanwhile, the review count indicates the total number of user reviews accumulated over time, serving as a proxy for a restaurant's visibility and popularity among diners. These two variables are widely recognized in the literature as core components of online reputation because they capture both the evaluative dimension (quality) and the social validation dimension (popularity). Empirical evidence shows that higher ratings significantly increase consumers' intention to visit a restaurant, while a larger number of reviews enhances perceived trustworthiness and credibility, reinforcing the restaurant's reputation in digital environments (Silva et al, 2021).

Research Design

This study employs an exploratory quantitative approach aimed at identifying hidden patterns among restaurants based on similarities in numerical attributes. The analysis was carried out in four main stages, namely:

1. Data Scrapping
2. K-Means Clustering — applied as an unsupervised learning approach to perform restaurant segmentation. This algorithm groups data into k clusters by minimizing the total Euclidean distance between each data point and its cluster centroid (Susanti et al., 2025). The K-Means algorithm can be summarized as follows (Salsabila & Leni, 2025):
   a) Determine the number of clusters (k) to be created.
   b) Randomly select k objects from the dataset as the initial cluster centers or centroids.
   c) Assign each observation to the nearest centroid based on the Euclidean distance (d_{eu}c) between the object and the centroid.

   $$d_{euc} = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \qquad (1)$$

   where x and y are two vectors of length n.
   d) For each cluster k, update the cluster centroid by calculating the new mean value of all data points within that cluster. The centroid of cluster k is a vector of length p that contains the average of all variables for the observations in that cluster, where p represents the number of variables.
   e) Minimize the total within-cluster sum of squares iteratively. In other words, repeat steps (c) and (d) until the cluster assignments no longer change or until the maximum number of iterations is reached.
3. The optimal number of clusters is then evaluated using four complementary metrics:
   a) Elbow Method, by analyzing the Within-Cluster Sum of Squares (WCSS) to identify a significant inflection point (Muayyad & Leni, 2025).
   b) Silhouette Score, used to assess internal cohesion and separation between clusters (Salsabila & Leni, 2025).
   c) Davies–Bouldin Index (DBI), which measures the ratio between inter-cluster distance and intra-cluster dispersion.
   d) Calinski–Harabasz Index (CHI), which evaluates the proportion of variance between and within clusters.

These four metrics are used complementarily to ensure that the segmentation results are not only mathematically optimal but also managerially interpretable.

4. Finally, the clustering results are visualized using a two-dimensional scatter plot, illustrating the position of each restaurant based on rating (X-axis) and review count (Y-axis). Each cluster is assigned a different color to facilitate interpretation. This visualization helps identify groups such as Star Performers (high on both variables) and Hidden Gems (high rating but few reviews). Then, digital reputation and sustainability insights will described for each cluster based on some literature.

Results And Discussion

Cluster Determination

Table 1. *Cluster Determination.*

k	WCSS	Silhouette	DBI	CHI
2	333.866	0.7246	0.5574	167.6962
3	185.5848	0.483	0.6712	257.3467
4	122.2288	0.5317	0.592	305.6533
5	84.9437	0.5576	0.5942	357.8165
6	66.3577	0.5273	0.6249	379.8962
7	57.0611	0.5314	0.5997	373.9379
8	46.3696	0.525	0.6022	401.5897
9	37.5824	0.5598	0.5763	439.5587
10	29.8684	0.5573	0.5337	497.2416

Based on the evaluation of cluster determination using four metrics, Within-Cluster Sum of Squares (WCSS), Silhouette Score, Davies–Bouldin Index (DBI), and Calinski–Harabasz Index (CHI), the best values were found within the range of k = 4 to k = 5. The WCSS value shows a sharp decline up to k = 4, followed by a gradual flattening, indicating that the elbow point lies around k = 4–5. Although the highest Silhouette Score appears at k = 2, this configuration tends to represent an overly simplistic separation and is therefore less suitable for more complex data structures.

Meanwhile, the low DBI value and the significant increase in CHI up to k = 4 suggest that the cluster separation is already quite optimal and that the data structure is more stable. Considering the balance between cluster distinction (Silhouette Score), cluster compactness (WCSS and DBI), and inter-cluster validity (CHI), the most ideal number of clusters is k = 4, as it provides the best equilibrium between model quality and analytical complexity.

K-Means Clustering Result

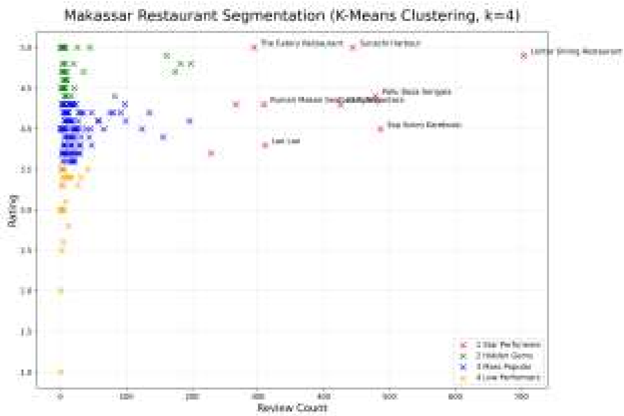

Figure 1. Clustering Visualization

Figure 1 presents the segmentation results of restaurants in Makassar using the K-Means Clustering method with four clusters (k = 4), based on two main variables: rating and review count from TripAdvisor users. Each color represents a different segment according to the restaurant's performance and popularity characteristics.

1. Star Performers (red) — Restaurants in this cluster have high ratings (≥4.5) and a large number of reviews (ranging from hundreds to more than 700). They represent the top-performing establishments in terms of both quality and popularity. Examples include *Lontar Dining Restaurant*, *The Eatery Restaurant*, and *Pallubasa Serigala*. These restaurants typically possess a strong reputation and serve as primary destinations for both tourists and local residents. There are 10 restaurants in this cluster.
2. Hidden Gems (green) — This cluster consists of restaurants with very high ratings (around 4.5–5) but a relatively small number of reviews. This indicates that while these restaurants are highly appreciated by their visitors, they remain relatively unknown to the wider public. This segment holds great potential for growth through digital promotion and visibility

enhancement. There are 77 restaurants in this cluster.

3. Mass Popular (blue) — Restaurants in this cluster receive a high volume of reviews but have average ratings (approximately 3.8–4.2). They are popular and frequently visited, yet the customer experience tends to be inconsistent. This segment could focus on improving service quality to maintain its large customer base while simultaneously increasing customer satisfaction. There are 147 restaurants in this cluster.
4. Low Performers (yellow) — Restaurants in this cluster have low ratings (below 3.5) and a small number of reviews. They represent the lowest-performing segment and may require significant improvements in food quality, service standards, or promotional strategies to remain competitive in the market. There are 37 restaurants in this cluster. There are 37 restaurants in this cluster.

Overall, this visualization helps identify the competitive positioning of each restaurant based on online consumer perception. The results clearly reveal a differentiation between restaurants that excel in quality and popularity and those that still require further development—providing valuable insights for marketing strategy formulation and service improvement initiatives.

Discussion

The segmentation patterns identified in Makassar show that differences between restaurant clusters are shaped not only by operational performance but also by socio-digital dynamics involved in building online reputation. Restaurants categorized as Star Performers tend to maintain consistent service quality while actively encouraging user-generated content, which strengthens credibility in digital platforms. Evidence from Park, Sutherland, and Lee (2021) demonstrates that online ratings and reviews directly contribute to consumer trust and intention to purchase restaurant services, highlighting the central role of digital reputation in shaping customer perceptions. High online ratings function as strong reputational signals for potential customers when selecting hospitality services, emphasizing the importance of maintaining positive digital feedback (Nain, 2025). Furthermore, online reputation significantly improves hotel profitability, indicating that strong digital credibility carries measurable economic value in the broader hospitality sector (Anagnostopoulou et al, 2020). From a socio-digital perspective, digital rating systems such as those used by Airbnb, operate as trust-building mechanisms that reduce uncertainty and facilitate interactions in platform-based economies (Christiaens, 2025). Taken together, these findings suggest that the sustainability of restaurant businesses is closely tied to their ability to cultivate a strong digital reputation, which supports economic sustainability through increased customer loyalty and social sustainability by fostering transparency and trust-based relationships between businesses and consumers.

Conversely, the restaurants categorized as Hidden Gems illustrate that strong service quality does not always translate into high digital visibility; with limited online exposure, high-performing restaurants may remain under-recognized within the digital ecosystem. This gap between quality and visibility underscores the importance of strategic digital storytelling and active management of online reviews to strengthen digital reputation. Research shows that effective management responses to online reviews influence customer trust and positively shape how potential guests perceive a business. Personalized and empathetic responses to online reviews significantly increase trust among potential customers who read those reviews (Kapeš et al, 2022). Likewise, Tan, Zou, and Li (2023) demonstrated that online review valence and volume have a measurable impact on hotel profitability, highlighting the economic significance of cultivating a strong digital reputation. These findings suggest that restaurants in the Hidden Gems segment hold strong potential to progress into higher-performing clusters if they can manage digital interactions more proactively and build a sustainable, credible, and ethical digital footprint.

Meanwhile, the Mass Popular segment illustrates how review-platform dynamics can turn digital popularity into both an asset and a vulnerability. When a restaurant accumulates many ratings and reviews, higher visibility on platforms such as TripAdvisor can boost demand, as shown by Lewis and Zervas (2019), who find that higher hotel ratings on major review platforms causally increase occupancy and revenue in the hotel industry. However, this increased exposure also amplifies the spread of negative experiences, so a large volume of reviews does not automatically imply high satisfaction. At the same time, research on hospitality risk management indicates that Corporate Social Responsibility (CSR) can mitigate reputational and business risks arising from negative ratings: Girardin, Bezençon, and Lunardo (2021) demonstrate that CSR cues soften the negative impact of poor online ratings on guest evaluations for hotels and restaurants, while Arora et al. (2020) argue that CSR in the hospitality industry functions as a form of risk management that supports long-term corporate sustainability. Therefore, restaurants in the Mass Popular cluster need not only to manage digital popularity and review volume, but also to align service quality, review responses, and CSR/ESG communication so that high online visibility is converted into durable, sustainable brand value rather than long-term reputational risk.

As for Low Performers, they represent establishments caught in a negative reputation cycle (few reviews, low ratings, and therefore minimal digital visibility). This pattern reflects a broader issue of digital inequality, where businesses with limited digital engagement or weaker online presence struggle to compete within platform-driven ecosystems. The UNCTAD Digital Economy Report (2021) highlights that unequal participation in digital platforms restricts economic opportunities, particularly for smaller enterprises that lack the resources and digital capabilities to increase their visibility and reach. Without efforts to strengthen their digital presence through consistent engagement, improved review management, and better online communication, restaurants in this segment risk remaining locked in a self-reinforcing cycle of low exposure and weakened digital reputation.

Overall, the findings of this study demonstrate that digital reputation and business sustainability reinforce each other. A strong digital reputation serves as social capital that enhances competitiveness and trust, while integrating responsible business practices such as corporate social responsibility (CSR) or sustainability initiatives adds moral legitimacy and long-term value to that reputation. In hospitality research, it has been shown that restaurants and hotels incorporating CSR and sustainable practices tend to foster better consumer perception and enhanced brand equity (Trinh et al, 2025). Moreover, when online review platforms highlight sustainability-related reviews such as environmental friendliness or responsible service practices, these aspects positively influence perceived helpfulness and reputation among consumers (Mariani, Borghi & Okumus, 2021).

These insights suggest that for restaurants to succeed in the digital era, it is not enough to rely solely on product quality or marketing; they must also manage their digital reputation ethically and transparently while embedding sustainability and responsible practices into their business model. Such an integrated approach helps build a fair, inclusive, and sustainable culinary business ecosystem in a rapidly digitalizing world.

Research Implications and Future Recommendations

Theoretically, this study contributes to literature on business data analytics, digital ethics, and sustainable digital transformation. It demonstrates that clustering algorithms can serve as tools not only for market segmentation but also for ethical evaluation of online reputation and consumer engagement. Practically, the study provides strategic insights for restaurant managers to develop transparent communication strategies, manage online reviews ethically, and balance promotional content with genuine service improvement. Future research should integrate sentiment analysis and Natural Language Processing (NLP) to capture emotional context from customer reviews, explore algorithmic fairness, and include spatial or geo-tagged data for location-based digital competitiveness analysis.

Conclusions

This study successfully categorized restaurants in Makassar into four distinct segments Star Performers, Hidden Gems, Mass Popular, and Low Performers using the K-Means clustering algorithm based on rating and review data from TripAdvisor. The segmentation not only demonstrated statistical validity through clustering performance metrics but also provided meaningful managerial insights into the dynamics of digital reputation and consumer engagement. The results highlight that success in the digital business ecosystem is not solely determined by popularity or service quality, but by the ethical management of data, transparency in communication, and responsiveness to customer feedback. By integrating data science techniques with the principles of digital ethics and sustainability, this study reinforces the importance of responsible innovation as a foundation for building a fair, trustworthy, and sustainable digital economy within the restaurant industry and beyond.

Conflict of Interest: The authors declare that there are no conflicts of interest concerning the publication of this article.

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