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Leveraging Hotel Reviews for Indirect Distribution Strategies: Insights from Badung Regency

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Abstract

Purpose: This study investigates the role of sentiment analysis in shaping hotel distribution strategies by analyzing online guest reviews in Badung Regency. The research examines how consumer sentiments correlate with ratings and their implications for optimizing distribution channels. **Research Design and Methodology:** Using VADER (Valence Aware Dictionary and Sentiment Reasoner), sentiment analysis was applied to hotel reviews collected from major online platforms. The extracted sentiment scores were analyzed to identify key trends that impact distribution effectiveness**. Results:** Findings indicate a strong prevalence of negative sentiments, particularly concerning cleanliness and staff behavior, which correlate with lower ratings. Positive sentiments highlight breakfast quality and staff friendliness. The results emphasize the influence of guest experiences on distribution channel performance, as negative reviews reduce a hotel's visibility and attractiveness on Online Travel Agencies (OTAs). Implications for Indirect Distribution Strategies: To counter negative sentiment, hotels must adopt proactive strategies, including reputation management, service enhancement, digital marketing, and targeted promotions. A data-driven approach is essential to improving online visibility, guest satisfaction, and overall market competitiveness in the hospitality industry. **Conclusion:** This study underscores the significance of sentiment-driven distribution strategies in the hospitality industry. Hotels in Badung Regency can leverage guest insights to refine their digital presence, improve conversion rates, and gain a competitive advantage in an increasingly data-driven distribution landscape.

Keywords: Badung Regency, Consumer Behaviour**,** Distribution Channels**,** E-WOM**,** Hospitality Marketing**,** Hotel Reviews**,** Sentiment Analysis

JEL Classification Code: L11, M31, Z32

1. Introduction

Tourism is a cornerstone of Bali specially Badung Regency's economy, with the hospitality sector playing a critical role. As hotels compete in an increasingly digitized market, their distribution strategies become key to reaching and engaging potential customers effectively. Distribution such as direct to consumer (D2C) in the hospitality industry refers not only to the physical or digital pathways through which services are sold but also to the role of consumer feedback in shaping their overall experience (McKee et al., 2023). Indirect channels, such as Online Travel Agencies

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(OTAs) like Booking.com, Expedia, and Agoda, play a crucial role in a well-optimized distribution strategy by providing maximum visibility, competitive pricing, and higher occupancy rates for hospitality businesses (Medina & Hadwick, n.d.). These platforms attract a global audience, leveraging their extensive marketing reach and consumer trust to drive bookings for hotels and event venues. OTAs also enable dynamic pricing strategies through data-driven algorithms that adjust rates based on demand, competitor pricing, and seasonal trends. However, while OTAs increase market exposure (Sharma & Nicolau, 2019), they often charge high commission fees, making it essential for businesses to balance OTA reliance with direct booking incentives.

Online Travel Agencies (OTAs), businesses can reduce commission costs, maintain control over pricing and promotions, and enhance customer relationships through personalized experiences. Moreover, the rise of digital platforms has amplified the influence of Electronic Word of Mouth (eWOM) (Thang & Quan, 2023), as guests share their experiences through online reviews, social media, and travel forums. Online reviews, a form of electronic word-of-mouth (eWOM), significantly impact how hotel services are perceived and distributed across various channels (Chen & Law, 2016). These reviews provide actionable insights for hoteliers to refine their offerings and adapt their distribution strategies. For instance, understanding tourist sentiments can guide decisions on platform prioritization, pricing strategies, and partnership development with intermediaries like OTAs (Online Travel Agents).

This study employs VADER sentiment analysis to evaluate hotel reviews in Badung Regency, aiming to uncover how sentiments influence ratings and how these insights can be integrated into effective distribution strategies. By identifying key pain points and strengths in guest feedback, hotels can enhance customer satisfaction and optimize their distribution approaches, ultimately contributing to the region's tourism growth.

Tourism plays a crucial role in the economy of Badung Regency, with the hospitality sector being a significant contributor. The quality of services provided by hotels is paramount in shaping tourists' experiences and satisfaction levels. With the rise of digital platforms, tourists increasingly share their experiences and opinions about hotels through online reviews. These reviews offer valuable insights into the strengths and weaknesses of hotel services.

Understanding tourist sentiment through hotel reviews is essential for hoteliers and policymakers to identify areas needing improvement and to enhance the overall guest experience. Sentiment analysis, a technique in natural language processing, allows for the systematic evaluation of these reviews by interpreting and classifying the emotions expressed in the text (Gunasekaran, 2023).

Recent advancements in sentiment analysis, particularly with the development of models like BERT and various deep learning approaches, have significantly improved the accuracy and efficiency of sentiment classification. For example, studies have shown that using BERT for sentiment analysis can effectively capture the nuanced sentiments expressed in hotel reviews, providing more reliable insights compared to traditional methods (Singgalen, 2025).

This study aims to explore the sentiment expressed in hotel reviews for Badung Regency, utilizing the VADER (Valence Aware Dictionary and Sentiment Reasoner) sentiment analysis tool. The objectives are to identify the predominant sentiments in these reviews, understand the relationship between ratings and sentiments, and analyze the sentiments across different travel groups and trip types.

The research design involves collecting hotel reviews from popular online platforms, processing the text data through VADER to obtain sentiment scores, and interpreting the results to provide a comprehensive overview of tourist sentiments. The findings of this study will offer practical implications for hoteliers in Badung Regency to improve their services and enhance guest satisfaction, ultimately contributing to the region's tourism development.

2. Literature Review

The analysis of sentiment in hotel reviews has garnered significant attention in recent years, driven by the growth of user-generated content on online platforms. Sentiment analysis, a subset of natural language processing (NLP), is utilized to interpret and classify emotions within text data, offering valuable insights into customer opinions and satisfaction.

2.1. Sentiment Analysis in Tourism

Sentiment analysis has been widely applied in the tourism industry to evaluate customer feedback and improve service quality. Previous studies have demonstrated the effectiveness of various machine learning and deep learning techniques in sentiment analysis. Similarly, BERT (Bidirectional Encoder Representations from Transformers) has been extensively used for its superior performance in understanding the context and nuances of sentiments expressed in short texts, such as online reviews (Gupta, 2024).

2.2. Techniques and Models

Several models and techniques have been explored for sentiment analysis in hotel reviews. Traditional methods, such as Naive Bayes and logistic regression, have been used with moderate success. However, deep learning approaches, particularly those utilizing neural networks like LSTM and convolutional neural networks (CNN), have shown significant improvements in accuracy and reliability (Vakalopoulou et al., 2023).

2.2.1. Traditional Machine Learning Techniques

Naive Bayes, logistic regression, and support vector machines (SVM) are among the traditional machine learning techniques that have been applied to sentiment analysis. These methods are relatively simple and computationally efficient but often lack the ability to capture complex linguistic patterns and contextual information in the text. For example, Naive Bayes and logistic regression for sentiment classification on big data, highlighting the utility of these models in handling large datasets but also noting their limitations in nuanced sentiment detection (Bahtiar et al., 2023).

2.2.2. Deep Learning Techniques

Deep learning techniques, particularly those involving neural networks, have revolutionized sentiment analysis by providing more sophisticated tools to understand and interpret text data. LSTM networks, which are capable of capturing long-term dependencies in text, have been particularly effective in sentiment analysis of reviews. The high accuracy of LSTM networks in classifying tourist reviews, showcasing their ability to handle the sequential nature of text data

The BERT model, developed by Google, represents a significant advancement in NLP. BERT’s bidirectional training approach allows it to understand the context of a word based on all of its surrounding words in a sentence, making it highly effective for sentiment. Studies have shown that BERT outperforms traditional machine learning models and other deep learning approaches in various NLP tasks, including sentiment analysis. For instance, implemented a BERT-based model for sentiment analysis of hotel reviews, achieving superior performance compared to other methods (Singgalen, 2024).

2.3. Application in Hotel Reviews

The application of sentiment analysis in hotel reviews provides actionable insights for improving customer satisfaction and service quality. By analyzing online reviews, hotels can identify common issues, understand customer preferences, and tailor their services accordingly (Toker, 2024). For example, sentiment analysis can reveal frequent complaints about cleanliness or staff behavior, allowing hotels to address these specific areas. Studies like those have demonstrated the utility of sentiment analysis in predicting review ratings and enhancing customer experience by providing personalized suggestions based on past reviews and ratings.

2.3.1. Identifying Common Issues

Sentiment analysis can highlight recurring issues in hotel services, enabling hoteliers to take corrective actions (Mehraliyev et al., 2022). For instance, a common complaint about cleanliness or unfriendly staff can be identified through the negative sentiments expressed in reviews. By addressing these issues, hotels can improve their overall guest satisfaction and enhance their reputation. This application of sentiment analysis has been validated in various studies, showcasing its practical utility in the hospitality industry.

2.3.2. Enhancing Customer Experience

By understanding the sentiments expressed in reviews, hotels can tailor their services to meet customer expectations better. Positive sentiments can indicate areas where the hotel is performing well, while negative sentiments can highlight areas needing improvement (Cristobal et al., 2024)For example, positive feedback about the quality of breakfast or the friendliness of staff can be leveraged to enhance marketing efforts. Conversely, addressing negative feedback about room cleanliness or noise levels can significantly improve the guest experience. The integration of sentiment analysis with recommendation systems has also shown promise in providing personalized suggestions to guests, further enhancing their experience (Zhang & Verma, 2017).

2.4. Challenges and Future Directions

The irregularity of online short comment sentences and the multilayered meanings of words pose significant hurdles. Future research is expected to focus on improving the robustness and accuracy of sentiment analysis models, potentially through the integration of more sophisticated deep learning techniques and larger datasets.

2.4.1. Handling Language Ambiguity

One of the primary challenges in sentiment analysis is dealing with the ambiguity and variability of language. Words can have different meanings depending on the context, and online reviews often contain informal language, slang, and abbreviations, making it difficult for models to accurately interpret sentiments (Ramalho et al., 2023).

2.4.2. Improving Model Robustness

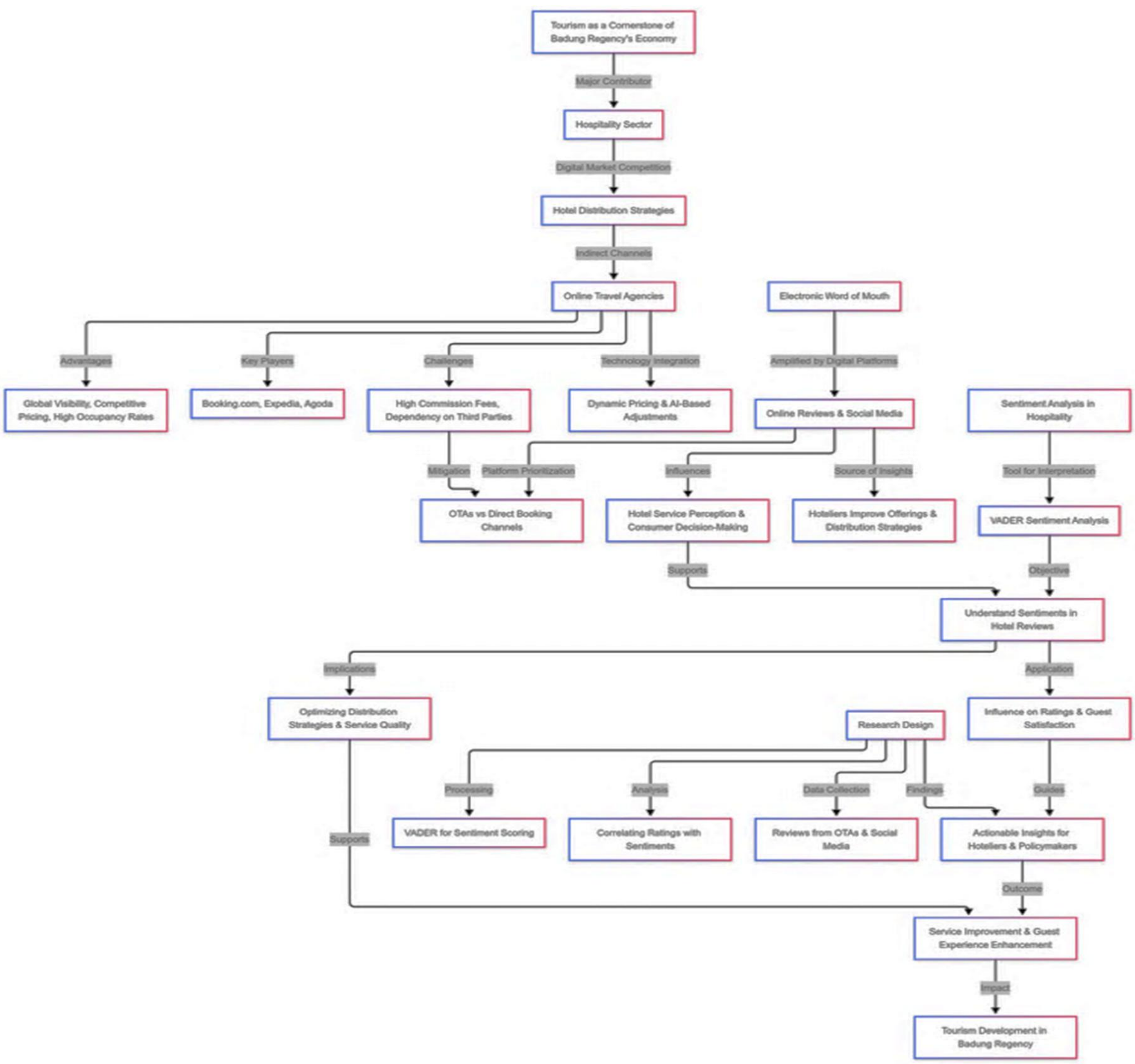
Ensuring the robustness of sentiment analysis models is crucial for their effective application in real-world scenarios (Riaz & Mehboob, 2024) This involves training models on diverse datasets that capture a wide range of linguistic expressions and contexts. Additionally, models need to be continuously updated to adapt to new trends in language use and to handle emerging forms of expression. Techniques such as transfer learning and continual learning could be employed to enhance model robustness and ensure they remain effective over time (Dixit, 2023).

2.4.3. Expanding Dataset Size and Diversity

The performance of sentiment analysis models can be significantly improved by training on larger and more diverse datasets (Mehraliyev et al., 2022). This would enable the models to capture a broader spectrum of sentiments and improve their generalizability. Collaborative efforts between academia and industry to share and utilize large datasets could facilitate this process. Additionally, incorporating multilingual datasets can help in understanding sentiments expressed in different languages, making the models more versatile and applicable in various geographical regions.

In conclusion, sentiment analysis has proven to be a powerful tool in understanding and improving customer satisfaction in the hospitality industry. The continuous evolution of NLP and machine learning techniques promises even greater insights and enhancements in the future. By addressing the current challenges and exploring new research directions, sentiment analysis can be further refined to provide even more accurate and actionable insights for the tourism and hospitality sectors.

3. Research Methods and Materials



Source : Research Findings, 2024.

Figure 1 : Research Mind Map

3.1. Understanding Sentiment Scores

VADER assigns three sentiment scores to a piece of text: positive: Measures the degree of positive sentiment. neutral: Measures the degree of neutrality. negative: Measures the degree of negative sentiment. These scores are normalized to add up to 1 (Youvan, 2007).

3.2. The Compound Score

The compound score is a single decimal value between -1 (most negative) and +1 (most positive). It attempts to summarize the overall sentiment of the text. VADER doesn't simply average the positive, neutral, and negative scores.

3.3. Calculation Steps

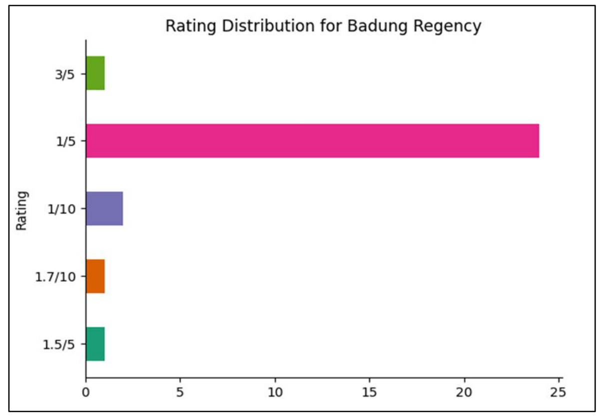
Lexicon Lookup:VADER checks each word in the text against its sentiment lexicon. This lexicon contains words and phrases associated with positive, negative, or neutral sentiment. Intensity Adjustment: VADER considers factors like capitalization (e.g., "GOOD" vs. "good") and punctuation (e.g., "bad!" vs. "bad") to adjust the intensity of sentiment for each word. For example, exclamation points and all-caps can indicate stronger emotions. Summation with Moderation: VADER sums the adjusted sentiment scores for all words in the text. However, it doesn't simply average them. The influence of each word's score on the compound score is moderated by a function that reduces the impact of scores closer to neutral. This helps to focus on the stronger sentiment aspects. Normalization: Finally, the sum of adjusted scores is normalized to a range of -1 to +1, providing the compound score.

3.4. Interpretation

A positive compound score (> 0.05) indicates overall positive sentiment. A negative compound score (< 0.05) indicates overall negative sentiment. A score close to 0 suggests neutral sentiment (Hoti & Ajdari, 2023.The compound score provides a concise overall sentiment indication. It considers both sentiment strength and intensity. Moderation helps focus on stronger sentiment aspects. In summary, NLTK's VADER compound score effectively captures the overall sentiment of text by combining sentiment lexicon lookup, intensity adjustment, moderated summation, and normalization.

4. Results and Discussion

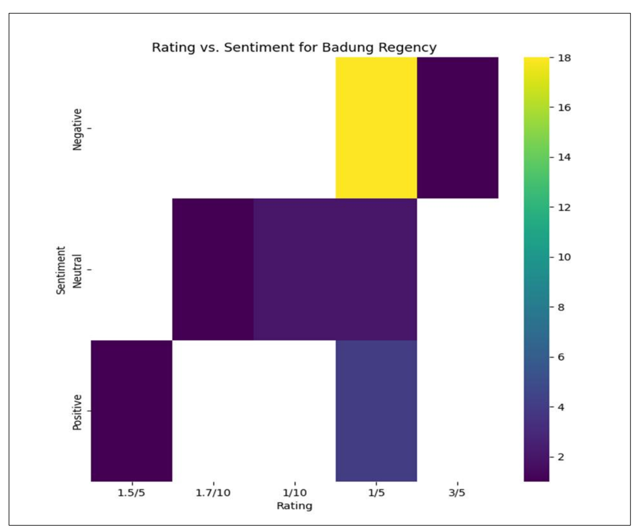
“Rating Distribution for Badung Regency” provides insights into hotel ratings based on reviews. Here’s a breakdown: Common Rating: The most frequent rating is 1/5, with nearly 25 reviews. This suggests significant dissatisfaction among guests. Other Ratings: Less common ratings include 3/5, 1/10, 1.7/10, and 1.5/5. These have fewer reviews. Overall Trend: The data skews toward lower ratings, indicating a general negative sentiment among reviewers.



Source : Research Findings, 2024.

Figure 2: Rating Distribution

Hotels in Badung Regency should address the root causes of poor ratings by improving service quality, cleanliness, and overall guest experience. Negative reviews on OTAs can reduce visibility in search rankings, decrease bookings, and lead to revenue losses (Aakash et al., 2024). A potential counter-strategy would be to actively engage with guests through personalized follow-ups and review management, ensuring a higher rate of positive feedback.

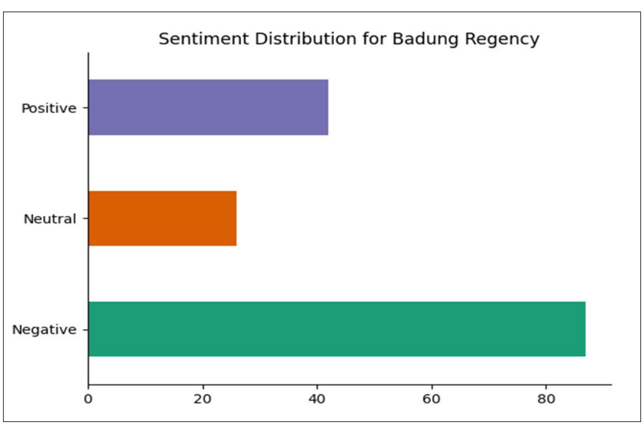


Source : Research Findings, 2024.

Figure 3: Rating Vs Sentiment

The bar chart titled "Rating vs. Sentiment for Badung Regency" shows the relationship between hotel ratings and sentiment categories (Positive, Neutral, Negative). Rating Categories: The ratings range from 1/5 to 3/5. Sentiment: Each rating category is broken down into sentiment categories: 1/5 Rating: Predominantly negative sentiment. 1.7/10 Rating: Mostly negative sentiment. 1/10 Rating: Overwhelmingly negative sentiment. 3/5 Rating: Mixed sentiments with some positive and neutral reviews. Frequency: The color gradient indicates the frequency of each sentiment within the rating categories, with darker colors representing higher frequencies. Overall, the chart highlights a trend where lower ratings are associated with negative sentiments, while higher ratings show a mix of sentiments. This suggests that guests who rated hotels poorly had negative experiences, whereas those who gave higher ratings had more varied experiences.

This correlation indicates that guests who rate hotels poorly tend to express their dissatisfaction more vividly, reinforcing the importance of reputation management on OTAs. Hotels should leverage sentiment analysis tools to monitor guest feedback and address recurring issues before they escalate (Ameur et al., 2023). Additionally, enhancing service training programs can ensure better customer interactions, leading to improved reviews.

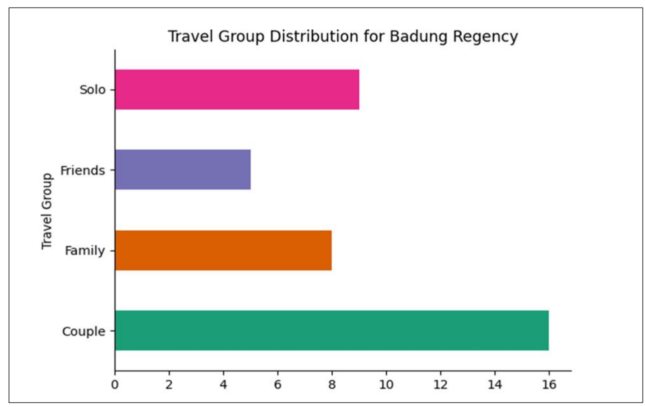


Source : Research Findings, 2024.

Figure 4: Sentimen

The bar chart titled "Sentiment for Badung Regency" shows the distribution of sentiments (Positive, Neutral, Negative) based on hotel reviews. Negative Sentiment: The longest bar represents negative sentiment, indicating that the majority of reviews are negative. Neutral Sentiment: The middle bar shows neutral sentiment, which is less frequent than negative sentiment but still significant. Positive Sentiment: The shortest bar represents positive sentiment, suggesting that positive reviews are the least common. Overall, the chart highlights a trend where negative sentiments dominate the reviews, indicating general dissatisfaction among guests in Badung Regency. This could be useful for identifying areas of improvement for hotel services in the region.

For **indirect distribution strategies**, this implies that Hotels must implement **active reputation management** by responding to negative reviews professionally and promptly (Park & Allen, 2013), Improving service quality could lead to more balanced sentiment (Astuti et al., 2023), Highlighting positive experiences through user-generated content can help counterbalance negative perceptions on OTAs (Magnani, 2020).

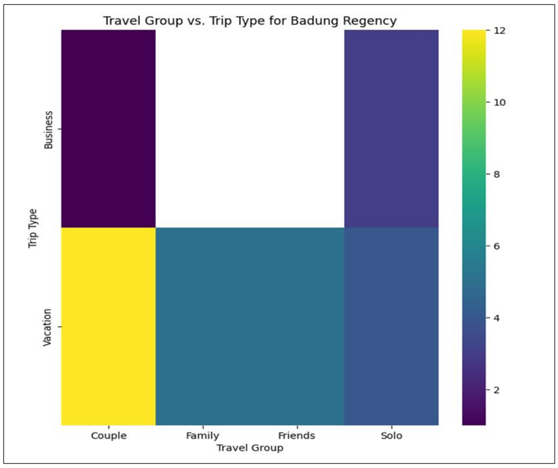


Source : Research Findings, 2024.

Figure 5: Travel Group Distribution

The bar chart titled "Travel Group Distribution for Badung Regency" shows the distribution of different types of travel groups visiting the area. Solo Travelers: Represented by the pink bar, solo travelers are the least common group, with the shortest bar indicating fewer individuals traveling alone. Friends: The purple bar represents friends traveling together. This group is more common than solo travelers but less common than families and couples. Family: The orange bar indicates family groups, which are quite common, with a significant number of families visiting Badung Regency. Couple: The green bar represents couples, which is the most common travel group, with the longest bar indicating the highest number of couples visiting the area. Overall, the chart highlights that couples are the most frequent visitors to Badung Regency, followed by families, friends, and solo travelers. This information can be useful for understanding the demographics of tourists in the region and tailoring services to meet their needs.

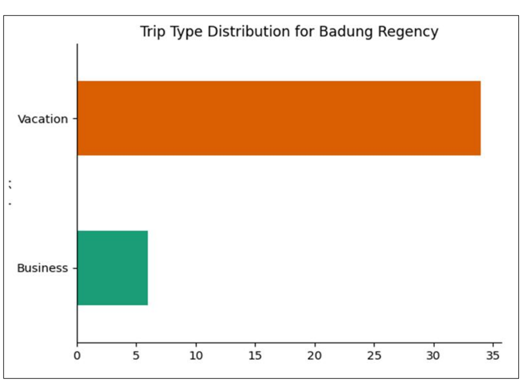
Understanding these demographics is essential for indirect distribution strategies. Since **couples and families dominate the tourism landscape**, hotels should tailor their marketing on OTAs (Murniati & Bawono, 2020) to emphasize **romantic getaways and family-friendly experiences**. Promotions targeting honeymooners, anniversary packages, or family vacation bundles could enhance conversion rates on digital platforms.



Source : Research Findings, 2024.

Figure 6: Travel Group Vs Trip Type

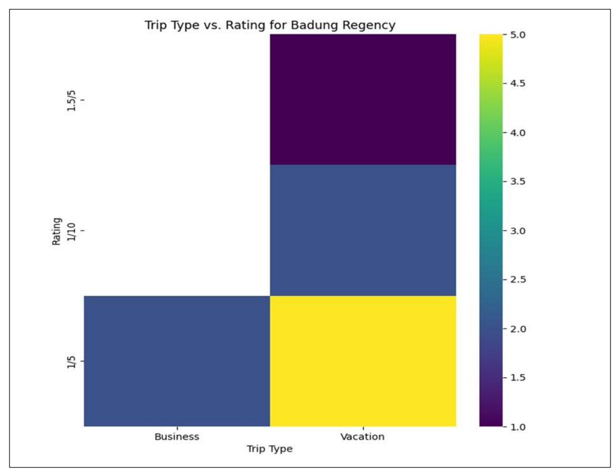
The stacked bar chart titled "Travel Group vs. Trip Type for Badung Regency" shows the relationship between different travel groups and their trip types. Travel Groups: The chart includes four travel groups: Couple, Family, Friends, and Solo. Trip Types: Each bar is divided into segments representing different trip types, such as Business and Vacation. Couple: Couples primarily travel for vacations, with a smaller portion for business. Family: Families mostly travel for vacations, with minimal business trips. Friends: Friends have a balanced mix of vacation and business trips. Solo: Solo travelers have a significant portion of business trips, but also travel for vacations. Overall, the chart highlights that vacations are the predominant trip type across all travel groups, with business trips being more common among solo travelers. This information can help understand the travel patterns and preferences of different groups visiting Badung Regency.



Source : Research Findings, 2024.

Figure 7: Trip Type Distribution

The bar chart titled "Trip Type Distribution for Badung Regency" shows the distribution of two types of trips: Vacation and Business. Vacation Trips: Represented by the longer bar, vacation trips are significantly more common, with the bar extending beyond the 30 marker on the x-axis. This indicates that the majority of trips to Badung Regency are for leisure purposes. Business Trips: Represented by the shorter bar, business trips are much less frequent, with the bar just past the 5 marker on the x-axis. This suggests that fewer people visit Badung Regency for business purposes. Overall, the chart highlights that Badung Regency is primarily a vacation destination, with a much higher number of leisure trips compared to business trips. This information can be useful for understanding the primary reasons people visit the area and for tailoring services to meet the needs of vacationers.



Source : Research Findings, 2024.

Figure 8: Trip Type Vs Rating

The bar chart titled "Trip Type vs. Rating for Badung Regency" compares the ratings of different trip types (Business and Vacation) in Badung Regency. Business Trips: There are two bars for business trips: One bar extends above the 4.5 mark, indicating very high ratings for some business trips. The other bar is much shorter, barely reaching above the 1.0 mark, indicating very low ratings for other business trips. Vacation Trips: There are also two bars for vacation trips: One bar reaches just below the 3.0 mark, indicating moderate ratings for some vacation trips. The other bar extends slightly above 1.5, indicating low ratings for other vacation trips. Overall, the chart shows a wide range of ratings for both business and vacation trips, with business trips having both very high and very low ratings, while vacation trips tend to have moderate to low ratings. This suggests varied experiences among travelers in Badung Regency.

Source : Research Findings, 2024.

Figure 9: The Word Cloud for Negative Feedback

The word cloud for negative feedback at a hotel in Badung Regency highlights the most frequently mentioned issues in guest reviews. Prominent Issues: The largest words, such as “dirty,” “poor,” “scam,” and “disappointing,” indicate the most common complaints. These suggest significant concerns about cleanliness, service quality, and potential fraudulent activities. Other Concerns: Words like “rude,” “unprofessional,” “waste,” and “uncomfortable” also appear frequently, pointing to issues with staff behavior, professionalism, and overall guest comfort. Emotional Impact: Terms like “disgusting,” “horrible,” “terrible,” and “frustrating” reflect the strong negative emotions experienced by guests. Overall, the word cloud provides a visual summary of the key areas where the hotel needs improvement to enhance guest satisfaction.

For hotels relying on OTAs and online reviews, addressing these issues is crucial because negative feedback reduces conversion rates—prospective guests often check recent reviews before booking. Hotels should adopt a crisis management approach, actively resolving guest complaints and using automated reputation management tools to track and improve guest sentiment.

Source : Research Findings, 2024.

Figure 10: The Word Cloud for Neutral Feedback

The word cloud for neutral feedback at a hotel in Badung Regency highlights the most frequently mentioned aspects of guest experiences. Prominent Aspects: The largest words, such as “room,” “food,” “check,” and “water,” indicate the most commonly mentioned topics. These suggest that guests frequently discuss their rooms, the food, the check-in/check-out process, and water-related amenities. Other Notable Terms: Words like “stay,” “booked,” “hotel,” and “pool” also appear frequently, pointing to general aspects of the hotel experience and amenities. Additional Context: Smaller words like “whirlpool,” “minutes,” “towel service,” and “backstage” provide further details about specific services and experiences mentioned by guests. Overall, the word cloud provides a visual summary of the key areas that guests talk about in their neutral feedback, offering insights into common topics and experiences at the hotel.

Source : Research Findings, 2024.

Figure 11: The Word Cloud for Positive Feedback

The word cloud for positive feedback at a hotel in Badung Regency highlights the most frequently mentioned aspects of guest experiences. Prominent Aspects: The largest words, such as “good,” “happy,” “excellent,” and “perfect,” indicate the most commonly mentioned positive sentiments. These suggest that guests frequently express satisfaction and delight with their experiences. Other Notable Terms: Words like “beautiful,” “kind,” “friendly,” and “wonderful” also appear frequently, pointing to the overall positive atmosphere and the quality of interactions with staff. Additional Context: Smaller words like “comfortable,” “relaxed,” “clean,” and “enjoyable” provide further details about specific aspects of the stay that guests appreciated. Overall, the word cloud provides a visual summary of the key areas that guests talk about in their positive feedback, offering insights into what makes their stay enjoyable and memorable.

For indirect distribution strategies, hotels should leverage positive feedback for marketing—highlight top-rated aspects in OTA descriptions and promotional campaigns (Zhang & Verma, 2017), Encourage guests to leave reviews—satisfied guests should be incentivized to share their experiences (Sugio, 2024). Use social media and influencer partnerships to amplify positive guest experiences, strengthening online presence (Kim & Kim, 2021).

Digital distribution has evolved significantly, transforming how hotels reach and engage with potential customers. The increasing reliance on Online Travel Agencies (OTAs) such as Expedia, Booking.com, and Agoda has reshaped the competitive landscape, making it crucial for hoteliers to optimize their presence across multiple platforms. Additionally, metasearch engines like Google Hotels and Trivago have gained prominence, enabling consumers to compare rates instantly and influencing purchasing decisions.

A key global trend is the shift toward direct booking strategies, where hotels aim to reduce dependency on third-party platforms by enhancing their own digital channels. Many hotel brands implement loyalty programs and personalized marketing strategies to incentivize guests to book directly through their websites. This approach not only reduces commission fees paid to OTAs but also strengthens guest relationships through customized offers.

Furthermore, the integration of artificial intelligence (AI) and big data analytics has revolutionized distribution management. AI-driven dynamic pricing, personalized recommendations, and chatbot-assisted customer interactions have become standard practices among leading hotel brands. These innovations enable hotels to predict demand patterns, optimize room rates, and provide seamless booking experiences.

Social media and influencer marketing have also emerged as powerful distribution tools. Platforms like Instagram, TikTok, and YouTube influence traveler preferences, with hotels leveraging influencer partnerships and user-generated content to boost brand visibility. Additionally, mobile-first strategies have become essential, given that a significant percentage of bookings now occur via mobile devices.

By linking these international trends to the study's findings in Badung Regency, we can observe parallels and identify areas where local hoteliers can adopt best practices. While sentiment analysis provides insights into customer preferences and areas for improvement, the integration of global distribution innovations such as AI-driven pricing, mobile booking enhancements, and personalized direct booking strategies could further refine hotels' competitive positioning.

5. Conclusions

This study highlights the integral role of sentiment analysis in informing hotel distribution strategies. The findings reveal a predominant trend of negative sentiments in guest reviews for hotels in Badung Regency, often linked to issues such as cleanliness and staff behavior. Conversely, positive sentiments emphasize areas like breakfast quality and staff friendliness, providing opportunities for marketing these strengths through targeted distribution channels.

The overall sentiment in Badung Regency, as reflected in online reviews, reveals a predominantly negative trend, with a high frequency of low ratings and dissatisfaction among guests. The most common complaints revolve around cleanliness, service quality, and trust issues, which significantly impact hotel reputations on Online Travel Agencies (OTAs) and other indirect distribution channels. Negative feedback not only reduces a hotel's visibility on OTAs but also influences potential travelers' decision-making, ultimately affecting booking rates and revenue. Despite this, positive reviews highlight strengths such as staff friendliness, comfortable stays, and quality services, offering opportunities for hotels to enhance their brand image and attract more guests.

To counteract these negative sentiments and improve their online presence, hotels in Badung Regency must adopt proactive indirect distribution strategies. These include : 1) reputation Management on OTAs – Actively monitoring and responding to guest reviews to address complaints and highlight service improvements, 2) Enhancing Service Standards – Addressing common concerns related to cleanliness and professionalism to reduce negative feedback, 3) Leveraging Positive Reviews for Marketing – Showcasing positive guest experiences through OTAs, social media, and user-generated content to shift public perception. 4) Optimizing Digital Distribution Channels – Strengthening direct booking incentives, metasearch engine optimization, and AI-driven pricing strategies to enhance hotel competitiveness. 5) Targeted Promotions for Key Traveler Segments – Catering to couples and families, the dominant traveller groups, with customized offerings that align with their expectations.

By integrating these strategies, hotels can effectively mitigate the impact of negative sentiment, improve their online reputation, and strengthen their market position in the competitive hospitality landscape. A data-driven approach to online sentiment analysis and guest feedback will be essential in ensuring long-term success in Badung Regency's tourism sector.

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