Research

Perceived Brand Value

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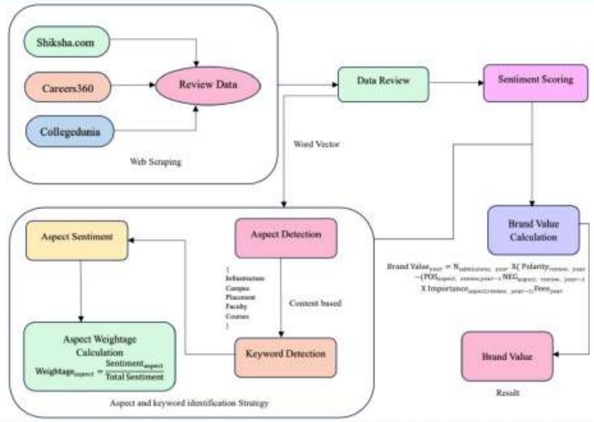
Abstract

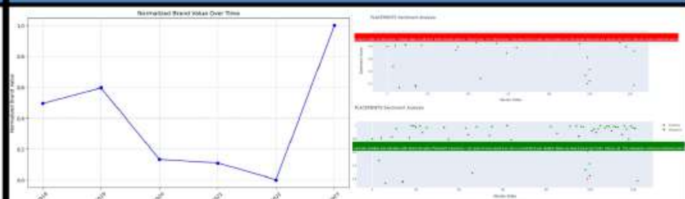
This project presents an innovative approach to evaluate the brand value of higher education institutions, focusing on the Don Bosco Institute of Technology (DBIT), Mumbai by harnessing sentiment analysis of online review data, we explore the impact of infrastructure, faculty quality, and placement opportunities on the institution's brand Value. Employing advanced natural language processing techniques and models like DeBERTa and RoBERTa for aspect-based sentiment analysis, our methodology quantitatively assesses the perceived brand value of DBIT. Through the analysis of student and alumni reviews,

This project constructs a brand value score reflecting the institution's brand recognition. Our findings offer actionable insights into the role of branding in higher education, highlighting the importance and effectiveness of data analysis in evaluating and enhancing institutional brand value.

System Architecture



Results



Insights into the evolution of DBIT's brand perception and value from 2018 to 2023. These fluctuations align with broader trends observed in the sentiment analysis across various aspects, indicating a complex interplay between DBIT's offerings and external factors influencing public perception

The aspect sentiment analysis plot, visually represents institution's review as a point, mapping the distribution of sentiment over time. The x-axis lists the reviews, and the y-axis shows the sentiment scores. This tool allows users to pinpoint specific content from the reviews, helping identify issues impacting brand value and student satisfaction, and highlighting areas for improvement.

Background Information

STUDY	METHOD APPLIED	LIMITATIONS
Perceived Quality of Products: A Framework and Attributes Ranking Method	PQAIR Method: Utilizes surveys and feedback to determine the importance of various product attributes via the Perceived Quality Framework (PQF), employing Best-Worst Scaling (BWS) and Choice-based Conjoint Analysis (CBC) to analyze consumer preferences. $S_p = 1 \ldots m = \sum_{i=1}^{n} \frac{a_i}{a_i}$	Subjectivity in Data Collection: The reliance on consumer surveys and feedback can introduce variability and bias, as perceptions of quality are highly subjective. Complexity of Design and Analysis: BWS and CBC methodologies require careful setup and interpretation, which can be complex and resource-intensive.
Research on Quantitative Model of Brand Recognition Based on Sentiment Analysis of Big Data for Laptops	Big Data Sentiment Analysis: Analysis of a large volume of consumer reviews from e-commerce platforms, using data preprocessing and clustering to extract sentiments and quality evaluations related to different laptop brands. $P(a,b) = \sqrt{a_i b_i} \cdot \sqrt{\frac{\sum_{i}^{n} z_i^m (r_{a_i} - r_{b_i})^2}{(n-1)(m-1)^2}}$ $Q(e,f) = \sqrt{e^2 - f^2} - \frac{2R(e,f)}{\lvert e\rvert - \lvert f\rvert}$	Data Quality Concerns: The exclusion of duplicate and non-relevant reviews requires rigorous data processing, which could still leave erroneous or biased data. Limitation in Sentiment Analysis: The technology used may not fully capture the nuances of human sentiment and could misinterpret sarcasm or context-specific comments.
Perceived Value and Purchase Intention of Counterfeit Luxury Brands: Testing the Moderation of Materialism	Survey-Based Quantitative Analysis: Researchers used a detailed questionnaire informed by existing scales to assess perceptions and intentions, applying factor analysis and regression models to test hypotheses, and hierarchical multiple regression to explore the moderation effect of materialism.	Generalization Issues: The findings may not be applicable beyond the sampled demographic, and the cross-sectional nature of the study limits the understanding of changes over time. Self-Report Bias: Responses are based on self-reporting, which can introduce bias and affect the validity of the results.

Algorithm

Step 1:Data Preprocessing:

We import necessary libraries including pandas, numpy, and nltk. Define functions for text preprocessing tasks such as removing punctuation, removing stopwords, and stemming. Define a function to handle negation in sentiment analysis.

Step 2:Sentiment Analysis:

We use the SentimentIntensityAnalyzer from nltk.sentiment module to calculate sentiment polarityDefine thresholds to categorize reviews as excellent, good, neutral, or negative based on polarity scores.

Categorize the reviews based on the defined thresholds.

Step 3: Data Preparation

We converted 'Year' column to integer type. Define years and categories for segmentation. Define conditions for categorizing reviews based on polarity.

Step 4: Brand Value Calculation

We calculate the brand value for each subset of data based on aspects such as placements, campus life, infrastructure, course, and faculty.

Incorporate fees data to calculate the final brand value for each category and year.Output the calculated brand values

Step 5:Average Aspect Scores

We defined aspects and years for analysis.Initialize a dictionary to hold the calculated sums for each year. Loop through each year and aspect to calculate the average aspect scores.Compute the sum for each year and aspect.

Step 6: Final Brand Value Calculation

$$\text{Brand Value}_{year} = \text{N}_{\text{admissions, year}} \text{ X}(-(\text{POS}_{\text{aspect, review,year}-1}\ \text{NEG}_{\text{aspect, review, year}-1}) \text{ X Importance}_{\text{aspect,review, year}-1)} \text{Fees}_{\text{year}}$$

Calculate the difference between positive and negative brand values for the year.Divide the difference by the sum of aspect scores for the year to get the final brand valueOutput the final brand values for each year.

References

[1].Khaloud Nasser Alsaid & Mahmoud Abdel Hamid Sale.2019. "Perceived Value and Purchase Intention of Counterfeit Luxury Brands: Testing the Moderation of Materialism", Amity Journal of Marketing 4 (1), (1-17).

[2].Kostas Stylidis, Casper Wickman & Rikard Söderberg .2020. "Perceived quality of products: a framework and attributes ranking method", Journal of Engineering Design, 31:1,37-67.

[3].Zhou L. "Research on Quantitative Model of Brand Recognition Based on Sentiment Analysis of Big Data". Front Psychol. 2022 May 12;13:915443.PMID: 35645872; PMCID: PMC9133927.

[4].Charitha Harshani Pereraa, Rajkishore Nayakb, and Long Thang Van Nguyen. 2022. "The impact of social media marketing and brand credibility on higher education institutes" Brand equity in emerging countries Journal of Marketing Communication 26: 1-26.

[5].Sedat Bastug, Vahit Calisir, Secil Gulmez, Alpaslan Ates .2022. "Measuring Port Brand Equity: A Sentiment Analysis on Social Media Messages", Dumlupinar University Of Social Science 65: 85- 106.

[6].Roberto Grandi, Federico Neri.2013. "Sentiment Analysis and City Branding". 1st International Workshop on Social Business Oct 2021.

[7]. Aulia, S. A., Sukati, I, & Sulaiman, Z. (2016). "A review: customer perceived value and its dimension." Asian Journal of Social Sciences and Management Studies. 3(2), 150-162.

[8]. Mitra, S., Jenamani, M. (2020). "A Method to Estimate Perceived Quality and Perceived Value of Brands to Make Purchase Decision Using Aspect-Based Sentiment Analysis". In: Saini, H., Sayal, R., Buyya, R., Aliseri, G. (eds) Innovations in Computer Science and Engineering. Lecture Notes in Networks and Systems, vol 103. Springer, Singapore.

[9]. .Mingchao Li, Bin Gong, "A Dynamic Evaluation Model of University Brand Value Based on Analytic Hierarchy Process", Scientific Programming, vol. 2022, Article ID 7602186, 10 pages, 2022.

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