Perceived Brand Value

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***Abstract*—The reputation and brand identity of higher education institutions hold paramount significance, influencing alumni, current students, prospective enrolls, and external organizations alike. Over the past two decades, institutions of higher learning have been subjected to rigorous evaluation, exemplified by publications such as News and World Report dedicating themselves to the annual ranking of the "best" colleges. In the context of this study, we have employed an adapted version of the Brand Equity Ten measures to formulate a model aimed at discerning the perceived brand value of Don Bosco Institute of Technology. Drawing from a wealth of data originating from online reviews on various college review platforms, our research entails an in-depth exploration of the salient factors contributing to the brand equity of academic institutions and the dynamic evolution of such brand equity over time. Our model provides a systematic methodology for quantifying and scrutinizing brand value, offering insights into the determinants that either enhance or diminish it. Through this analytical approach, we seek to contribute to a nuanced understanding of the intricate dynamics surrounding the brand equity of higher education institutions.**

Brand and academic quality of an institution of higher education are interrelated criteria to attract the right talent both as faculty members as well as the students, the gainers to the institution. This paper is an attempt to examine (a) the branding of higher education institutions, (b) different factors of branding of higher education institutions, (c) the effect of branding on the acquisition of the right talent, (c) the impact of branding of higher education institutions.

Key Words: Perceived Quality, Perceived Value, Brand Management, Aspect-Based Sentiment Analysis, Online Consumer Reviews, Brand Perception

I. Introduction

A) what is perceived brand value?

Perceived brand value, an intangible yet profoundly influential concept, encapsulates the collective judgment and assessment of a brand's merit, reputation, and overall position as discerned by consumers and the wider market sphere. It is the synthesis of individual perceptions shaped by a myriad of factors, including direct experiences, interactions, and passive observations. This multifaceted perception is molded by several core elements: the perceived quality of products or services offered by the brand, the reputation the brand has meticulously cultivated through its actions and communicative endeavors over time, and the comprehensive image the brand projects, which includes its visual identity and the messaging it disseminates. Additional pivotal factors include the caliber of customer experiences, the emotional resonance the brand manages to forge with its audience, and the influence of social proof, such as reviews and endorsements, in sculpting the brand's perceived value. Moreover, consumers' evaluation of the brand's value proposition, particularly how it balances price against perceived quality, plays a crucial role in shaping their perceptions of brand value. It is worth noting that perceived brand value is inherently subjective and can exhibit variability across different consumer demographics and market contexts.

B) why is there a need for perceived brand value?

The necessity for cultivating and enhancing perceived brand value emerges from its profound impact on guiding consumer behavior, fostering brand loyalty, and shaping the competitive advantage of a brand within the marketplace. In an era characterized by heightened market competition and information overload, the ability of a brand to distinguish itself through a high perceived value can determine its market success and longevity. This perceived value acts as a critical decision-making criterion for consumers, guiding their choices in a cluttered market landscape. It not only influences initial purchase decisions but also plays a vital role in building long-term customer relationships, fostering brand loyalty, and encouraging repeat purchases.

II. Literature Survey

"Sentiment Analysis and City Branding" (2013) explores the relationship between sentiment analysis and city branding, with a particular focus on the city of Bologna. It identifies tangible features, such as porticos, as significant elements in the city's branding strategy. The paper highlights Bologna's perception as a friendly city, renowned as the capital of food and music in Italy. Notably, the study introduces a novel approach by associating ice cream with Bologna as a means to promote its ice cream culture. Emphasizing the horizontal dimension in sentiment analysis and knowledge mining, the paper leverages social media data collected from 2012 to 2013 to gain insights into Bologna's brand image and public sentiment, offering valuable insights into the intersection of sentiment analysis and city branding with a unique focus on a specific city's characteristics and culture[1]

"Perceived quality of products: a framework and attributes ranking method" (2019) presents a comprehensive design research study centered on the domain of product quality perception, with a specific focus on Original Equipment Manufacturers (OEMs) in the automotive industry. This study employs a diverse range of data collection methods, including semi-structured interviews, unstructured conversational interviews, informal discussions, and internal document examination, to delve into the intricacies of perceived product quality. It introduces an innovative objective and subjective ranking method to assess the significance of various attributes associated with perceived product quality. By combining expert opinions and customer data, the research offers a holistic perspective. The study's broad sample size comprising eight European and two North American automotive OEMs, with their global reach and emphasis on premium and luxury market segments, ensures a representative dataset. The identification of attributes through in-depth exploration, interviews, workshops, and pilot experiments enriches the analysis, ultimately providing a robust framework and methodology to comprehend and rank perceived product quality attributes within the automotive industry[2]

“The paper titled "Measuring Port Brand Equity: A Sentiment Analysis on Social Media Messages" (2020) delves into the assessment of brand equity in seaports by employing sentiment analysis on social media data. It leverages social media sentiment analysis to gain a deeper understanding of customer perceptions and interactions related to port brand equity. The research utilizes content from social media platforms, including Twitter, to analyze and evaluate the brand equity of seaports, offering valuable insights into the significance of social media interactions and sentiment in shaping the image and reputation of these critical entities in the shipping and maritime industry[3]

“The Impact of Social Media Marketing and Brand Credibility on Higher Education Institutes' Brand Equity in Emerging Markets" (2022), investigates the interplay between marketing strategies, social media activities, and customer-based brand equity within Higher Education Institutions (HEIs) in Sri Lanka and Vietnam. Grounded in the Elaboration Likelihood Model, the study empirically explores the relationship between social media marketing efforts and brand credibility, with a multi-dimensional approach to customer-based brand equity in the higher education sector. Drawing data from HEIs in both Sri Lanka and Vietnam, the research collects and analyzes information related to marketing strategies, social media activities, brand credibility, and perceptions of customer-based brand equity. In doing so, it sheds light on the complex dynamics of brand equity in emerging markets, particularly within the context of higher education institutions in these two countries[4]

"Research on Quantitative Model of Brand Recognition Based on Sentiment Analysis of Big Data for Laptops" (2022), employs web crawler technology to collect laptop brand information from e-commerce platform reviews. It meticulously follows a data preprocessing and sentiment dictionary construction process, enhancing its methodology through word vector-based attribute extension. Utilizing unsupervised deep learning and neural networks for text quantization, the study then performs an algorithm evaluation that involves similarity calculation and machine learning models. The paper's empirical analysis is conducted on a vast dataset of 437,815 user reviews of laptops spanning from January 2019 to December 2021. After preprocessing, 297,264 refined reviews are utilized, with 10% designated for training and testing, while the remaining 267,538 data points are reserved for forecasting brand recognition based on sentiment analysis, offering a comprehensive and data-driven approach to understanding consumer perceptions and brand recognition within the laptop market[2

II. System Design

1.Web Scraping:

web scraping module to collect online consumer reviews of DBIT from various platforms such as educational portals, review websites platforms, and forums. Utilize web scraping libraries such as BeautifulSoup or Scrapy in Python to extract relevant data from web pages.

2. Platform Selection and Data Collection:

Identify and select the platforms where online consumer reviews of DBIT are available. Configure the web scraping module to extract review text, user ratings, dates, and other relevant metadata from these platforms.

3. Sentence Preprocessing;

We define a function preprocess_sentence aimed at preprocessing sentences, specifically for sentiment analysis related to a given aspect (e.g., "placement"). The preprocessing includes emphasizing sentiment-related words and handling negations.

3.1 Lowercasing:
The input sentence and aspect are converted to lowercase to ensure uniformity and case-insensitive processing.

3.2Aspect-specific Sentence Extraction:
Using regular expressions (re. find all), the function extracts parts of the sentence that mention the specified aspect. These parts are identified as sentences or sentence fragments containing the aspect and ending with a period. If the aspect isn't found, the entire input sentence is considered relevant to the aspect.

3.3Sentence Preprocessing:

Function: preprocess_sentence(sentence, aspect, positive_words, neutral_words, negative_words)

Preprocesses the input sentence focusing on the specified aspect, by emphasizing sentiment-related words (positive, neutral, negative) and adjusting for negations.

3.3.1Negation Handling: If negations are detected (via contains_negation function), occurrences of "not " and "no " are modified to "not_" and "no_", respectively, emphasizing negation during sentiment analysis.
Function: contains_negation(sentence)

It iterates through a predefined list of negation words (['no', 'not', 'none', 'cannot', 'without']). If any of these words are found in the input sentence (converted to lowercase for case-insensitive matching), the function returns True; otherwise, it returns False.

3.3.2Emphasis on Sentiment-related Words:

The function searches for positive, neutral, and negative words within the sentence. When found, it emphasizes these words by repeating them three times. This repetition makes the sentiment more pronounced for sentiment analysis models.

3.3.3Combining Pre-processed Sentences:

The pre-processed aspect-specific sentences are combined into a single string, separated by spaces.

3.4 Tokenization:

we utilize the absa_tokenizer function to process text inputs in a specific format tailored for the Aspect-Based Sentiment Analysis (ABSA) model. This involves incorporating special tokens like [CLS] and [SEP], along with the preprocessed sentence and the targeted aspect, such as "infrastructure". The return_tensors="pt" argument ensures that the tokenized output is provided as a PyTorch tensor, a requisite format for the ABSA model.

we analyze the sentiment towards the "infrastructure" aspect based on the preprocessed sentence. This assessment reveals the model's perception of sentiment, categorizing it as negative, neutral, or positive. Our findings underscore the impact of preprocessing techniques, such as emphasizing sentiment-related words and addressing negations, on influencing the sentiment analysis outcome. This highlights the importance of preprocessing methods in enhancing the interpretability and accuracy of sentiment analysis results.

3.5 Model Prediction:

The absa_model(**inputs) function sends the tokenized inputs to the ABSA (Aspect-Based Sentiment Analysis) model. This model then predicts the sentiment scores for the aspect "infrastructure" based on the given sentence. The model's output, called logits, provides raw scores for different sentiment categories without normalization. These scores indicate the model's assessment of how positive, negative, or neutral the sentiment is regarding the infrastructure aspect mentioned in the sentence.

3.6 Probability Calculation:

The logits are passed through a softmax function (F.softmax), which converts them into probabilities. Each probability corresponds to the model's confidence in each sentiment class (negative, neutral, positive) for the aspect "infrastructure".

probs. detach().NumPy ()[0] detaches the probabilities from the computation graph (making them no longer require gradients), converts them to a NumPy array, and selects the first (and only) element of the array, which contains the sentiment probabilities

4. Aspect-Based Sentiment Analysis :

Aspect-based sentiment analysis framework to analyze the sentiment of reviews based on predefined aspect categories such as college life, infrastructure, placement, faculty expertise, etc. integrates the collected reviews from the web scraping module into the sentiment analysis pipeline.

4.1 **DeBERTa: Decoding-enhanced BERT with Disentangled Attention and XLM-Robert:**

We set up two sentiment analysis models: one specifically designed for Aspect-Based Sentiment Analysis using the DeBERTa v3 architecture, and another for traditional sentiment analysis using XLM-RoBERTa. These models can be used to analyze the sentiment of text data in different contexts and for different purposes

4.2 Aspect Relevance Assessment:

The preprocessing function intelligently assesses the relevance of a specified aspect within the context of an input sentence by examining related keywords. This ensures that aspect-based sentiment analysis is conducted only when the specified aspect is deemed relevant based on the presence of related keywords.

4.3 Aspect-Specific Sentiment Analysis:

The sentiment analysis function conducts aspect-specific sentiment analysis by leveraging the preprocessed sentence and identifying sentiment scores for the specified aspect. This targeted approach enables detailed insights into sentiment towards specific aspects, enhancing the granularity of sentiment analysis results

5. Brand Value Calculation:

We are calculating brand values by integrating sentiment analysis data with historical fee information across different categories ('pos' and 'neg') and years (2018 to 2023). It first prepares the fee data and ensures compatibility of the year column in the sentiment analysis dataset. Then, it iterates through each category and year, filtering the data based on polarity conditions and calculating brand values by considering sentiment scores, importance factors, and associated fees. Finally, the code outputs the calculated brand values for each category and year combination, facilitating a comprehensive analysis of brand perception over time.

$$Brand\ Value_{year} = N_{admissions,\ year}\ X$$
$$(\ Polarity_{review,\ year-1} - (POS_{aspect,\ review,year-1} - NEG_{aspect,\ review,\ year-1})\ X\ Importance_{aspect,review,\ year-1})Fees_{year}$$

$N_{admission,\ year}$ is the number of admissions in the given year.

$Polarity_{\ reivew,year-1}$ represents the average sentiment polarity of all review from the proceeding years.

$POS_{aspect,\ review\ ,\ year-1}$ and $NEG_{aspect,review,\ year-1}$ are the positive and negative sentiment scores, respectively, from a given aspect in reviews from the preceding year.

$Importance_{aspect,\ review,\ year-1}$ reflects the Weight or the importance of that aspects as derived from the review of proceeding years.

$Fees_{year}$ is the fee charged by the institution in the given year.

IV. SYSTEM WORKING

1.Testing and Evaluation :

1.1 Testing with different review:

Sr.no	username	Review	year
1	Siddharth Pundeer	Placement Experience: After the sixth semester.	2023
2	Khushal Rathod	Course Curriculum Overview: It is my dream to ...	2019

3	Prakash kanaram patel	Course Curriculum Overview: From when I was a ...	2020
4	Erwin Dsouza	Placement Experience: Companies like L&T, Info...	2021

Table 1:Scraped review from various sites

a function preprocess_sentence designed to preprocess sentences for aspect-based sentiment analysis, emphasizing positive, neutral, and negative words, and modifying negations for clarity. However, it now includes a check to see if the aspect is mentioned in the sentence at all. If the aspect is not mentioned, the function returns None, indicating that the sentence should be skipped for analysis regarding that particular aspect.

Aspect Detection: The function attempts to find sentences within the text that specifically mention the aspect in question. It uses regular expressions to search for any sentence fragments containing the aspect.

Negation Handling: If negations like "not", "no", "never", or "none" are found within those sentences, the code modifies these negations by appending an underscore (e.g., "not " becomes "not_"). This is likely intended to make these negations more distinct for the model, potentially helping it better understand the context of negation.

Word Emphasis Through Repetition: The function identifies positive, neutral, and negative words within the aspect-specific sentences and emphasizes them by repeating them three times. This could be a strategy to make the sentiment expressed by these words more pronounced, possibly aiding the model in recognizing the sentiment more clearly.

Aspect Absence: If the aspect is not mentioned in any part of the sentence, the function returns None. This is a crucial step, as it allows the calling code to decide not to perform sentiment analysis for this sentence-aspect pair, under the rationale that if the aspect isn't mentioned, any sentiment analysis on it would be irrelevant.

Skipping Analysis for Unmentioned Aspects: The example usage checks if the preprocessed sentence is None, indicating the aspect wasn't mentioned. It then skips the sentiment analysis for that aspect, as seen in the conditional check that prints a message about skipping analysis if preprocessed_sentence is None.

1.2Sentiment Analysis of Different Aspects

sentiment analysis results for different aspects. The sentiment scores, including positive and negative sentiments, are plotted against the review index for each aspect. The aspects considered in the analysis include placements, campus life, infrastructure, course, and faculty. Each subplot in the visualization represents one aspect, with positive sentiment scores plotted in green and negative sentiment scores plotted in red. The layout of the subplots ensures clear distinction between sentiment trends for each aspect. This visualization offers insights into sentiment variations across different aspects, aiding in the understanding of overall sentiment patterns within the dataset.

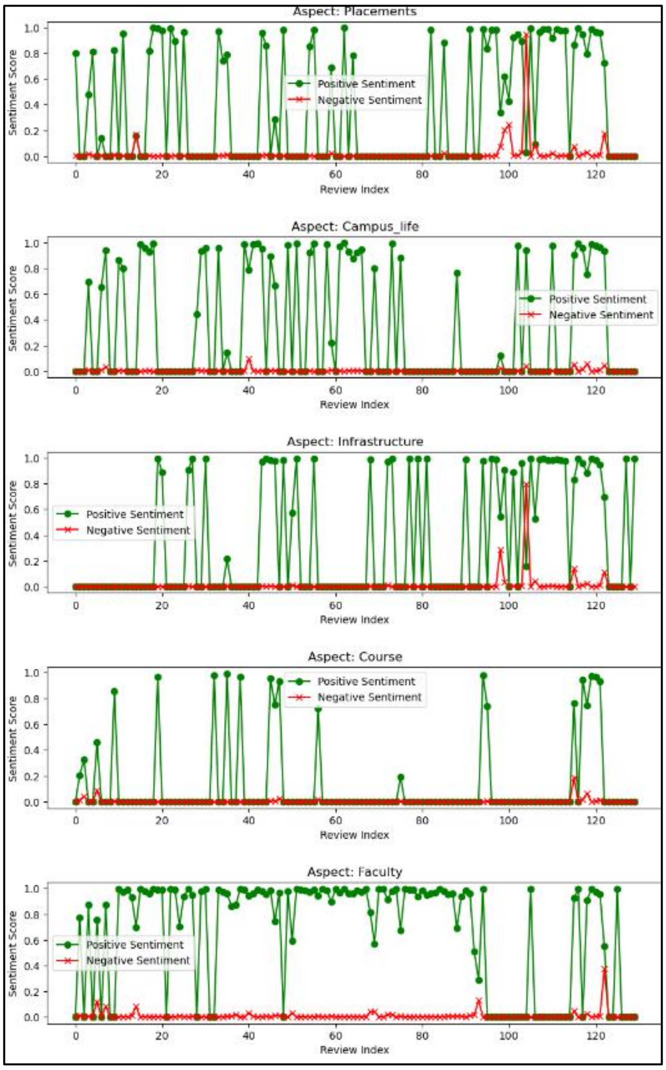

Fig1.Sentiment annlysis of different aspect

1.3 Calculation of brand value

review data to calculate the average sentiment values for each aspect and year, computes the sum of aspect scores for each year, and finally calculates the final brand values based on the difference between positive and negative brand values normalized by the aspect sum. The result is a set of final brand values for each year, reflecting the overall sentiment towards different aspects of the brand over time.

```
Year 2018: Brand Value = 810647.3730335854
Year 2019: Brand Value = 934862.1157947223
Year 2020: Brand Value = 1256604.8044996713
Year 2021: Brand Value = 1558525.7915556466
Year 2022: Brand Value = 10962469.182710044
Year 2023: Brand Value = 580000.0
```

Fig2.brand value as per year

1.3 Normalized Brand Values over year using Number of review

The brand values are normalized using min-max normalization. This normalization process scales the brand values to a common range between 0 and 1, making them directly comparable regardless of the number of reviews. The resulting normalized brand values offer a standardized measure of brand performance over time, taking into account both sentiment analysis results and the influence of review volume.

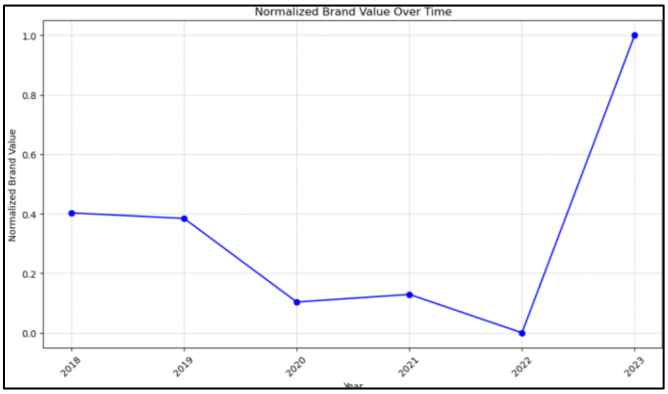

Fig 3 Normalized Brand value Over Year

After visualizing the trend of normalized brand values over time, it appears that there was a decline in brand values in 2022. This decline could potentially be attributed to various factors, due to the COVID-19 pandemic, there might have been disruptions in the institution's operations, including limitations on in-person activities, closures, or changes in policies. These disruptions could have affected the institution's ability to collect reviews during that period, leading to a lower number of reviews available for sentiment analysis. As a result, the decrease in available data could contribute to the decline in brand values observed in 2022.

2. User interface(UI)