ABSA Supported Interactive Dashboard for Hospitality Decision Support

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Abstract

The explosion of user-generated content in the form of hotel reviews has spawned a large volume of data that can be exploited to enhance decision-making in the hospitality sector. Aspect-Based Sentiment Analysis (ABSA) is a beneficial approach for understanding cus-

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tomer reviews, allowing businesses to know how people feel about particular aspects like cleanliness, service, and location. Yet, such insights are rarely exploited unless presented in an intuitive manner. This paper reviews our semantic-aware framework for ABSA to address contextual ambiguity in aspect-level sentiment analysis and proposes an extension of our existing work by integrating the existing ABSA framework with an intelligent interactive dashboard. The ABSA output is modeled using Power BI, a leading business intelligence tool, to support effective decision-making. We design a three-layer interactive dashboard that facilitates three major stakeholders i.e., clients (guests), web site owners, and hotel owners. Each stakeholder is provided with customized insights making them knowing much more in very little time. The proposed system can be considered a bridge between data analysis and decision-making. Usability evaluation is performed to assess the effectiveness of the proposed dashboard. Experimental results demonstrate the effectiveness of the dashboard for decision support in the hotel industry.

Keywords: Visualization, Dashboard, Sentiment analysis, Hotel industry.

1. INTRODUCTION

A lot depends on the clients real-time feedback for improving the service quality and better decision-making [1]. Online platforms like TripAdvisor and Booking.com are very effective sources for client's feedback, suggestions and opinions. The huge volumes of these opinions on such platforms makes it difficult for businesses to extract actionable insights manually. Aspect-Based Sentiment Analysis (ABSA) [2, 3] is the task of analyzing sentiments and extracting sentiments on specific aspects a the services. However, ABSA alone is not sufficient for hotel industry managers to take effective decisions [4]. The insights generated must also be presented in a clear, interpretable manner [5] for quick and reliable decision making. Therefore, in this paper, we extend our unique ABSA approach by introducing an interactive dashboard that visualizes the results in a user-friendly format. The highlights of the ABSA approach are presented in this paper along with the design of the interactive dashboard developed using state-of-the-art tool of Power Bi. The evaluation of the interactive dashboard is conducted using usability testing. This dual focus of this work ensures that the extracted insights can directly support managers and stakeholders in making informed, data-driven decisions.

The ability to know the feelings of the customers at the bottom line is necessary to the industries such as hospitality where the quality of services and their satisfaction with the service are directly connected to revenue. Although the traditional sentiment analysis approaches provide a broad view of the opinion of customers [6, 7], it is frequently unable to recognize sentiments related to particular features of a product or service, for example, cleanliness, service, or location. This weakness has led to the emergence of Aspect-Based Sentiment Analysis (ABSA), which entails a more detailed analysis. Nonetheless, there is a substantial research gap in the successful management of word sense ambiguity in ABSA [8, 9]. The meaning of a word, such as predictable or sharp, will have diverse connotations within a context and the traditional models cannot disambiguate these meanings. Even though there has been partial effort to include Word Sense Disambiguation (WSD) in sentiment analysis, little research has been done on the application of WSD in ABSA. The current techniques are usually domain constrained and computationally expensive [9, 10, 11]. Thus, more scalable, more accurate, and more context-aware ABSA models which are effective in solving polysemy and improving aspect-level sentiment classification are needed.

Simultaneously, a similarly large but a less studied gap is in the visualization of ABSA results [12, 13]. Though studies have been made into the accuracy of the ABSA model, minimal attention is made on presentation of the results in a meaningful and actionable manner to the decision-makers. The majority of ABSA products are distributed in still or written formats, which do not provide much assistance in strategic business understanding. In industries such as hospitality that particularly depend on customer satisfaction data, such a deficiency in the provision of visualization instruments that are intuitive, interactive, and real-time would constitute a major drawback, especially when managers and analysts must process a wide range of sentiment data with limited time. The existing visual strategies can hardly be filtered in terms of time or location or customer group or can be used as a drill-down solution to investigate a specific review or observe specific aspect trends.

Thus, the proposed study targets both of these research gaps: first, by reviewing our proposed ABSA framework already published in [14], which integrates WSD with contextual embeddings to achieve a better sentiment classification at the aspect level; and second, by creating an interactive dashboard that can visualize these insights in an easy-to-use format, which would close the gap between the results of sentiment analysis and decision-making.

The rest of the paper is structured as follows. Section 2 gives highlights of the related work. Section 3 presents the proposed framework. Section 4 present the experimental setup and discusses the results. Section 5 presents the visualization and decision support framework. Section 6 provides the usability evaluation and analysis. Finally, Section 7 concludes the paper and highlights future research directions.

2. RELATED WORK

2.1 Aspect-Based Sentiment Analysis (ABSA)

There are lots of existing literature on the topic of ABSA, however there are only few previous works that have proposed different ways to visualize customer feedback such as word clouds, heatmaps, and interactive dashboards [15]. In this section, we describe literature review for both of these tasks.

Recent developments in ABSA have attempted to address the issue of legitimacy and scale with the assistance of deep learning models and graph-based methods. For example, Wang et al. [16] emphasize that training task-specific models either fail to exploit the shared knowledge among multiple ABSA tasks effectively or neglect the complementarity between tasks. Besides this, they also focus on quadruple extraction and triple extraction. To target these challenges, Wang and his team proposed UnifiedABSA. The experiments show that UnifiedABSA can consistently outperform existing models on all tasks. Similarly, another ABSA contribution is the work reported in [17]. This work investigates the performance of machine learning algorithms for a specific classification task. Support Vector Machine (SVM) and Logistic Regression (LR) were compared. The results indicate that Support Vector Machine achieved superior accuracy (87.34%) compared to Logistic Regression (84.64%), suggesting Support Vector Machine as a more suitable option. Another latest contribution for ABSA involves usage of LLM i.e. large language models [18]. A couple of existing work (e.g., [19]) consider few-shot ABSA, but they do not specifically focus on few-shot ABSA, which is the main focus of this study.

Implicit sentiment data is abundant in the ABSA datasets, of which the sentiment polarity is difficult to identify since there are no clear opinion words. To address implicit sentiment, [20] introduces an ABSA method that combines explicit sentiment augmentations for more sentiment clues. They introduced an explicit sentiment generation on ABSA to generate such augmentations. Experimental results indicate the performance of our approach outperforms the baselines in both implicit and explicit sentiment accuracy. For more comprehensive review of ABSA, [4, 8] are recommended readings.

2.2 Visualization and Decision Support Systems

Visualization plays a critical role in transforming complex datasets into actionable insights. While visualization tools such as Power BI, Tableau, and D3.js have been widely used to analyze customer feedback and improve decision-making, we could find no such work which combines ABSA and visualization in a single framework. Only few works that somehow can be related to this work are discussed in this sub-section. For example, Ghosal et al. [21], proposed a weighted ABSA framework that uses Word2Vec and extended OWA operators to visualize customer feedback in the tourism industry. Their approach enables businesses to identify key aspects that influence customer satisfaction and prioritize improvements accordingly. Besides this, [22] developed visualizations to observe the relations between aspect ratings and customer satisfaction (overall ratings) before and during the pandemic. The methods, strengths, and limitations of the state-o-the-art techniques are highlighted in TABLE 1.

In summary, the existing sentiment analysis approaches entail detailed analyses in terms of the opinions of customers; however, very few focus on visualization and any type of info-graphics for decision support systems.

3. Review of the Proposed Framework

3.1 System Overview

This section outlines the already proposed and published framework for semantic-aware aspect-based sentiment analysis tailored to the hospitality sector [14]. The FIGURE 1 highlights the overall system while FIGURE 2 clarifies the contributions of different modules and also disambiguates the contributions of [14] and this work. The proposed interactive dashboard is then integrated with output of this ABSA framework. The key components to effectively tackle challenges like contextual ambiguity and aspect-level sentiment classification and visualization are described in separate subsections.

Study	Technique / Approach	Strengths	Limitations
Wang et al. [16]	Unified ABSA (multi-task learning)	Improves performance across multiple ABSA tasks and captures task relationships	Limited exploitation of semantic ambiguity; lacks visualization support
Siddiqua et al. [17]	Machine learning (SVM, Logistic Regression)	Simple implementation and effective baseline performance	Limited contextual understanding; less effective for complex language
Lu et al. [18]	LLM-based augmentation (QAIE)	Enhances few-shot learning and improves contextual representation	Computationally expensive and resource intensive
Ouyang et al. [20]	Explicit sentiment augmentation	Improves detection of implicit sentiment and enriches sentiment clues	Does not explicitly resolve word sense ambiguity
Chang et al. [22]	Visualization with deep learning-based ABSA	Provides insights into sentiment trends and relationships	Focuses mainly on visualization with limited model innovation
Nadeem et al. [14]	Semantic ambiguity resolution in ABSA	Addresses ambiguity in natural language and improves interpretation	Limited integration with deep learning and graph-based methods
Ghosal et al. [21]	Weighted ABSA with Word2Vec and OWA	Supports prioritization of aspects and integrates visualization	Limited contextual modeling and semantic understanding
ABSA Surveys [4, 8]	Survey-based analysis	Provides comprehensive overview of methods and challenges	Lacks implementation and integrated solutions

Table 1: A systematic review of state-of-the-art approaches in aspect-based sentiment analysis and visualization

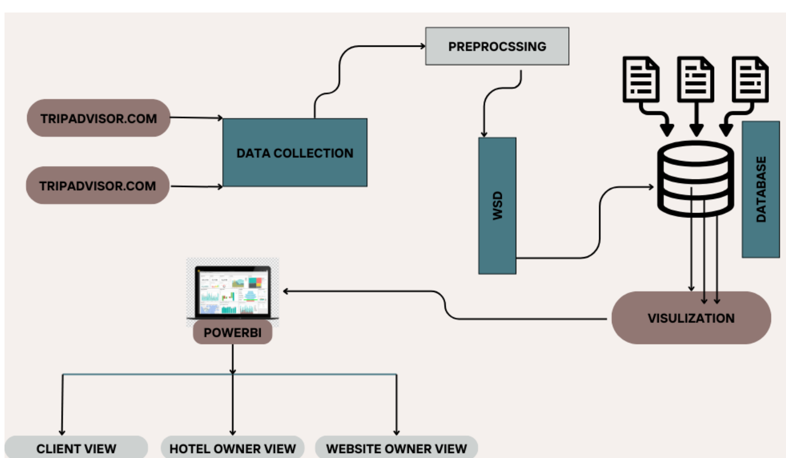

Figure 1: Block diagram of the overall system

3.2 Dataset Description and Preprocessing

The data collection used i.e., RABSA and its comparison with existing benchmark SemEval is given in TABLE 2.

Sr. No	Dataset	Positive		Negative		Neutral	
		Train	**Test**	**Train**	**Test**	**Train**	**Test**
1	SemEval 2014 [23]	2164	728	807	196	637	196
2	RABSA [14]	1000	500	1000	500	1000	500

Table 2: Class Distribution of the RABSA and SemEval2014 [14]

3.3 Data Acquisition

RABSA was collected manually from online platforms of Booking.com and TripAdvisor. Reviews from each category were collected. Overall, 4,500 reviews were collected, comprising of 1,500 reviews of each sentiment type. The pre-processing of the reviews was performed using standard methods.

3.4 Data Annotation

The RABSA was annotated by two experts both having M.Phil degrees in English linguistics. The Cohens Kappa score of 0.81 was obtained which suggests a high level of inter-annotator agreement [24].

3.4.1 Data annotation guidelines

The annotators were provided with predefined guidelines to ensure consistency and reliability. The guidelines are given below:

- Sentence-Level Sentiment: If a sentence is expressing satisfaction, praise, or a favorable opinion, a positive label was assigned, while if a sentence is expressing dissatisfaction, criticism, or an unfavorable opinion, a negative label was assigned. A sentence was labeled as neutral if it contained any factual information.
- Aspect Identification: Annotators recognized different features of the hotel or hotel related services such as room, cleanliness, staff, location, food, service, facilities, or price.
- Aspect-Level Sentiment: The polarity of the sentiment related to an aspect was identified. For example, in the sentence ”The room was clean, but the staff was unhelpful,” the aspect *room* was labeled positive, whereas staff was labeled negative.
- Multiple Aspects: Different aspects were identified if a sentence mentions more than one aspects.

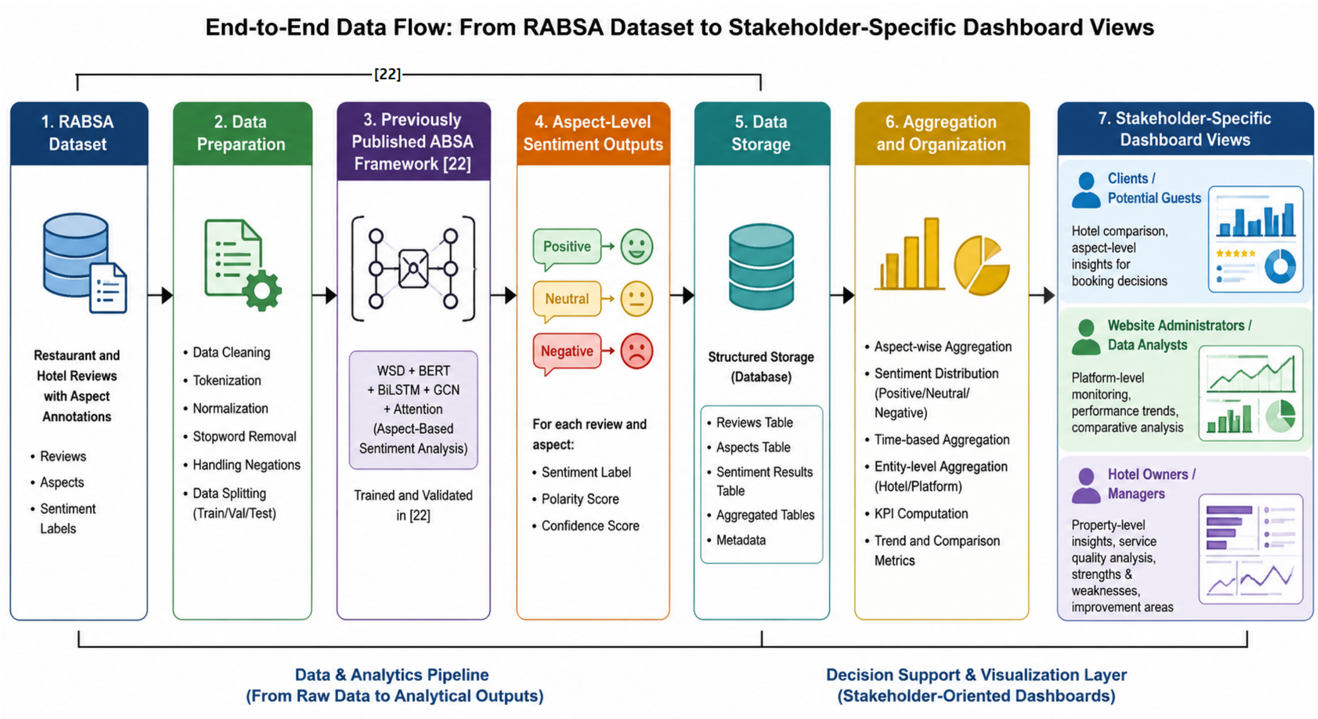

Figure 2: Component Level Diagram of the System

- Contextual Interpretation: Annotators considered the context and intended meaning of the sentence, including common expressions and informal digital communication. Sarcasm, negation, and contrastive expressions were interpreted based on the overall meaning conveyed by the reviewer.
- Neutral Cases: Sentences that only provided information without expressing an subjective opinion were assigned a neutral label.
- Ambiguous Cases: If anything i.e. aspect or sentiment was unclear, annotators reviewed the context and applied the predefined guidelines consistently.

3.5 Structure of the RABSA Dataset

RABSA (Refined Aspect-Based Sentiment Analysis) [14] follows the XML format. Each <sentence> element has a unique sentence ID (sid), a related review ID (rid), and its sentiment polarity (positive, negative, etc.). The text of the sentence is mentioned in a <text> tag, while all extracted aspects are listed within <aspect> elements. Each aspect annotation includes the term, word position, polarity, and category, allowing for detailed sentiment analysis at multiple levels. Compared to the SemEval dataset structure, RABSA offers several refinements:

[label=•]

1. It labels both aspect and sentence-level polarity.

2. It simplifies annotation by removing the <aspectCategories> tag and merging the category into the <aspect> tag.
3. It replaces character-based positioning with word-level indexing, improving annotation consistency and ease of processing.

3.6 Model Overview

In this section, we review our already proposed and published hybrid model [14] of an Aspect-Based Sentiment Analysis (ABSA) system based on Word Sense Disambiguation (WSD), BERT embeddings [25], BiLSTM [26], Graph Convolutional Networks (GCN), and an attention model to improve the accuracy of sentiment prediction on an aspect level. Let S represent a sentence from a hotel review, and A an aspect (e.g., cleanliness, staff, location). The idea is to estimate the semantic orientation (SO) of the aspect A provided the sentence S that is mathematically formulated as:

$$P(SO(A)|S) \tag{1}$$

The issue of word ambiguity can be discussed as in this model, a word such as predictable or bank can have different sentiments depending on the situation a WSD module is introduced. It takes BERT embeddings to obtain the context representation of a word and matches it with sample sentences of WordNet through cosine similarity. The most similar sense is chosen as the one that was correct to interpret to.

The WSD module generates contextual BERT embeddings for target words and compares them with WordNet's gloss examples. Cosine similarity is used to select the most appropriate sense:

$$S_{\text{selected}} = \arg\max_i \left(\text{CosineSimilarity}(E_W, E_{S_i})\right) \tag{2}$$

This method ensures more accurate sentiment analysis by resolving polysemy, especially important in aspect-level sentiment interpretation.

WordNet serves as the external lexical knowledge base, offering synsets, part-of-speech tags, glosses, and semantic relations like hypernyms, hyponyms, antonyms, and usage examples. These are crucial for selecting the right sense of a word in context.

3.7 System Architecture and Implementation

The ABSA system provides sentiment-coded results that are saved in a centralized SQL database. Power BI gets data from this database and it is updated either at set times, or in real time.The dashboard is meant for three types of users: clients (i.e., the end-users), the website/platform owner, and hotel owner. Power BI [27, 28] is selected for this research due to its robust set of features that cater to real-time, interactive, and user-friendly data visualization.It provides a simple connection to various data sources like SQL databases, flat files, and APIs among others. Its inherent abilities to model and transform data and interactive filtering make it conducive to transferring the results of ABSA to visual dashboards that are useful to business analysts. What's more, because Power BI is cross-platform, and because it can share this capability with others, it's perfect for shared use among several people.

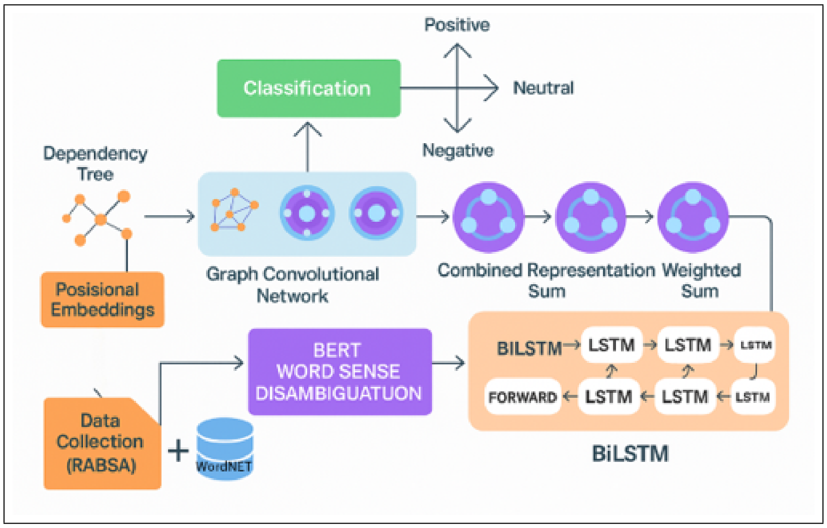

Figure 3: Architectural Diagram of ABSA System as published in [14]

4. RESULTS AND DISCUSSION

This section presents the results of the ABSA work published in [14]. TABLE 3 report the performance numbers of the machine learning models (VSM, random forest, Naive Bayes, BiLSTM, GCN) as well as the best models reported in the literature (as quoted) and the one published in [14]. These metrics are divided into positive, negative, and neutral, and the associated accuracy (Acc.) and F1 scores in percentage. The model achieved superior performance over all the models with an accuracy of 90.52, 89.12, and 84.32, and an F1 score of 85.03, 86.05, and 71.06 in positive, negative, and neutral classes, respectively. The rows of TABLE 3 are the models that will be applied to the sentiment analysis. The first row contains VSM, and the last row are our proposed model and baseline models, which contains random forest, naive Bayes, BiLSTM, GCN, several previous best models. The accuracy and F1 scores of the models are presented in three sentiment categories. The best model serves as the reference in all the three categories.

Model	Positive		Negative		Neutral	
	Acc.	F1	Acc.	F1	Acc.	F1
VSM	81.00	78.03	80.13	78.43	76.39	69.89
Random Forest	79.01	68.13	77.83	67.47	78.39	68.70
Naive Bayes	79.01	74.38	74.83	68.43	73.19	68.10
BiLSTM	80.42	76.03	81.12	78.05	77.52	69.08
GCN	78.02	70.15	76.03	68.45	71.88	65.78
SenticGCN (Liang et al., 2022)	86.92	81.03	82.12	79.05	85.32	71.28
ABSA Approach of [14]	**90.52****	**85.03****	**89.12****	**86.05****	**84.32***	**71.06***

* and ** indicate statistical significance levels, where * denotes $p < 0.05$ and ** denotes $p < 0.01$.

Table 3: Performance comparison of the approach presented in [14] with baselines

5. VISUALIZATION AND DECISION SUPPORT FRAMEWORK

5.1 Design objectives

The integration of visualization into the ABSA framework serves several core objectives:

[label=•]

1. Actionable Decision Support: Stakeholders such as hotel owners, booking platform managers, and clients can quickly identify strengths and weaknesses at the aspect level.
2. Enhanced Interpretability: Visualization improves the transparency and understandability of the ABSA results, allowing even non-technical users to comprehend trends and patterns.
3. Comparative and Temporal Insights: Through visual comparisons across time, geography, and competitor benchmarks, users can derive deeper, strategic insights.

5.2 Stakeholder-Oriented visualization

5.2.1 Client dashboard

The user's need to be able to discover good hotels quickly based on as granular feedback from previous customers as possible. This perspective assists trip planners in more informed booking decision making by exposing salient ratings of individual aspects (e.g., ”cleanliness” or ”location”). The client dashboard was tailored toward the empowerment of the end-users, e.g. hotel guests or potential customers, by offering them an easy and interactive display of the metrics of hotel performance. The dashboard focus is put on plainness, interpretability, and actionable information so that clients can make a wise decision regarding what to stay in. The dashboards are interactive, built in Power BI, and enable the user to filter information based on the name of the hotel, year of stay and season, which means that the analysis of the data will be personalized based on the needs of the user.

FIGURE 4 illustrates a complete picture of the client dashboard where the various hotel performance indicators are shown combined together. The aspect of quality of food, comfort of rooms, cleanliness, safety, friendliness of staff, location, check-in experience, and quality of the services are the most important service attributes that have been highlighted using the simplified measures. Pie charts and bar charts offer sufficient visual representation of overall dimensions of services on average, and year-to-year comparison of total experience gives the clients an opportunity to monitor stability and service delivery enhancements. Seasonal comparisons can also be shown, which provides customers with ideas regarding the differences in experiences in various seasons of the year (summer, winter, fall, spring). These visualizations can be especially helpful to travelers who schedule their travels by season and would like to decide their anticipations based on historical data.

Figure 5 is a narrower analysis of the hotel performance, as it is limited to the spring season. The dashboard is a map of experiences of the clients in the chosen hotels during this time frame, and it

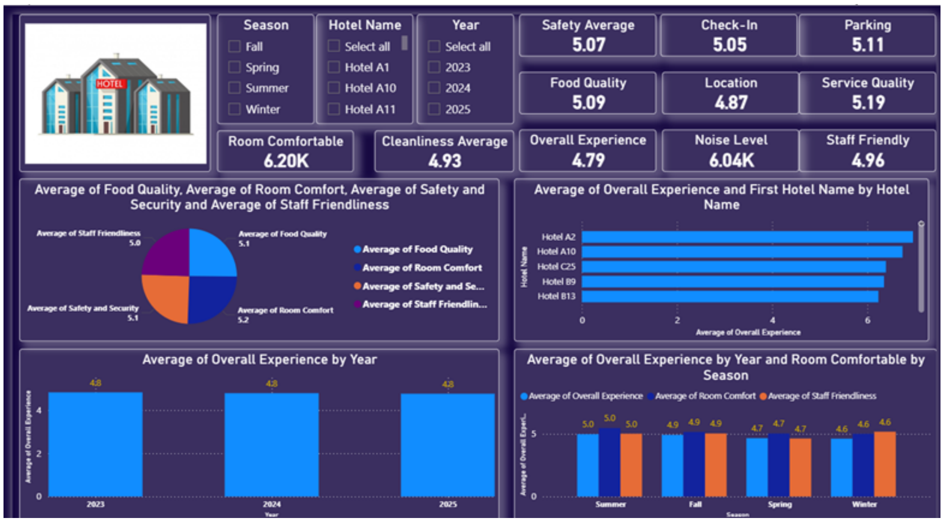

Figure 4: An overview of the client dashboard

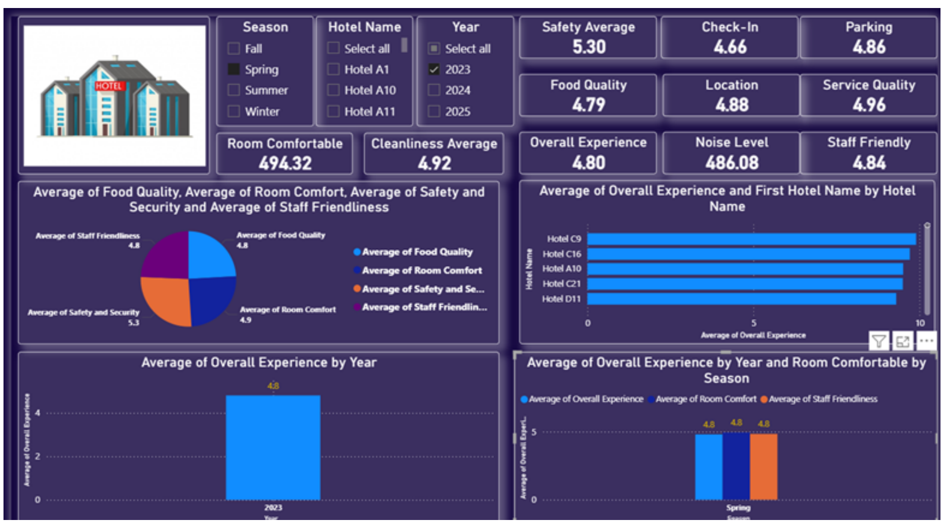

Figure 5: Overview of Client Dashboard

allows users to compare a particular aspect of safety, friendliness of staff, and general comfort during a certain season. This filtered visualization assists in the decision-making of clients who would like to travel in the spring and want to compare the various hotels in that regard. The dashboard will remove noise by displaying average values at any given dimension and therefore the clients will only be able to access the most relevant information in their planning.

The hotel-specific view is shown in FIGURE 6 with the dashboard zooming into the performance. of Hotel A10. In this case, service factors like food quality, friendliness of staff and comfort of the rooms. have significantly better ratings than the more general averages presented in FIGURE 4. By isolating the measures of a single hotel, the client can assess the effectiveness of a certain property. corresponds to their anticipation of service quality. The granular view is specifically useful when

Figure 6: An overview of the hotel specific view

the customer is short listing a hotel brand and needs more premise of its performance on various qualities until an ultimate booking decision has been made.

5.2.2 Website owner dashboard

The managers of websites and the reservation systems need to have a microscopic view of the hotels to run. search and optimization of platforms. Their dashboard gives an idea on customer. trends of satisfaction, trend of destination and performance bench marking. The dashboard of website owners gives them a platform wide view, which consolidates the performance. intelligence in all the hotels listed. This is a more advanced perspective that is dedicated to general bookings, revenue. generation, review counts, and sentiment distribution, which provide a clear picture of platform administrators. image of the customer satisfaction and business results.

The interactive dashboard reveals the aggregate statistics across the platform, which is total bookings, total revenue, number of reviews, and average sentiment scores. One of the central panels displays sentiment distribution (positive, neutral, negative), allowing the owners of the given websites to see a summary of the trends of traveler satisfaction rates on all the properties. This kind of consolidated view can be used to monitor health of the platform and its growth over time.

This dashboard also provides support for financial and operational decision making. It demonstrates trends in the monthly volumes and revenue of the bookings, and the comparative ranking of the hotel performances demonstrates in which hotels the business is most moved. This intelligence enables the owners of hotels websites to analyze the marketing campaigns, optimize the partnerships, and allocate the platform resources to the hotels that create the most interest and income.

In this case, the dashboard as illustrated in fig 7 is doing a relative sentiment analysis between hotels. Visualizations (bar or radar charts) indicate which hotels receive relatively more positive or negative feedback. Sentiment distribution in conjunction with booking/revenue stats, helps website owners

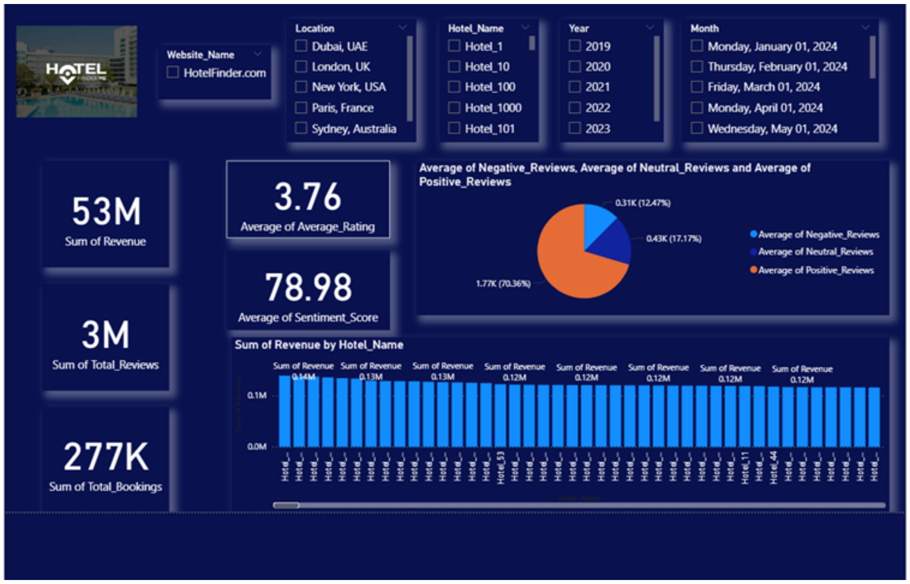

Figure 7: A sentiment-based illustration of hotel comparison

to identify underperforming hotels and work with them to improve quality of services. Success stories or examples of best-practice of high performing hotels can also be showcased.

5.2.3 Hotel owner dashboard

The owners of hotels enjoy the personalized analytics of their property and their competitors. The dashboard allows seeing the direct insights of customer satisfaction at the aspect level and monitoring the financial and reputational performance over time.

The dashboard of the hotel owners is specifically designed, as it offers to the managers and property owners a complete performance monitoring tool. In contrast to the client dashboard that is centered on customer decision-making, that of the owners is centered on operational insights. It enables the hotel owners to see the strengths, weaknesses and make the evidence-based decisions to enhance the level of satisfaction of the guests and the quality of the services. The system would translate textual reviews into measurable metrics to be used by owners of the system in the continuous improvement of the system by incorporating the outputs of sentiment analysis into the layered Power BI dashboards.

The dashboard provides performance of hotels in various dimensions of service. quality. The major factors that can be used to assess quality include the quality of food, comfort of the rooms, cleanliness, safety, friendliness of staff, etc. The location, check-in experience, and the general quality of the service are presented in the consolidated form. Average customer experience scores also attract attention to the dashboard and assist hotel owners. compare the performance of their hotel with that of other hotels in the industry or to compare it to that of. competitor properties. The seasonal trends and year on year comparisons are constructed such that the owners. can monitor the fluctuation of satisfaction amongst guests, periodically monitoring time when the service advances.

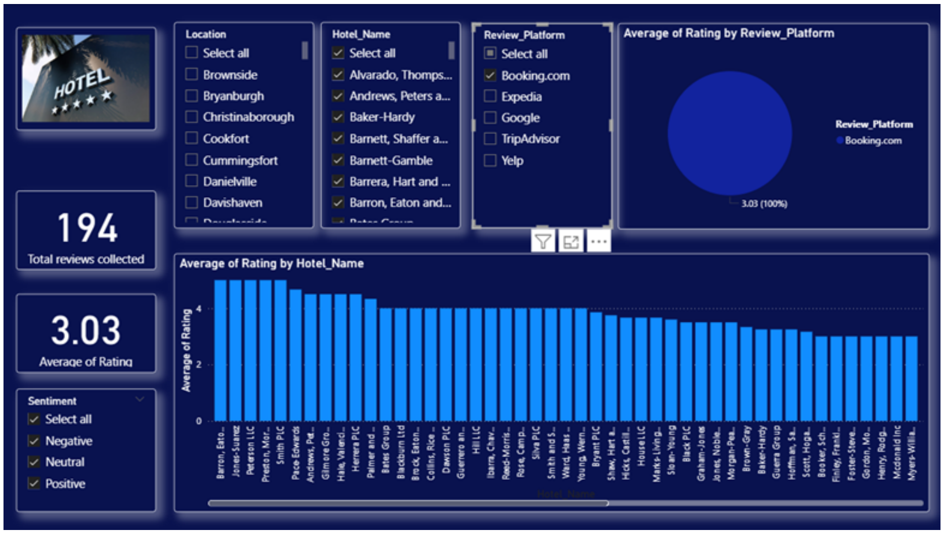

Figure 8: An illustration of performance and business analysis with granular drill-down through review-oriented hotel standings.

most necessary. This overview is a high level perspective or a management snapshot, which gives the snapshot of the management. image of the well-being of the hotel.

The dashboard also provides the seasonal performance insights that indicates the extent of variation of the quality of the service based on the months of the year. As an example, the dashboard will display the trends of spring quarterly performance which could reveal whether staff responsiveness during the busy tourism season is an issue or whether the cleanliness may be observed to decline during the season of active attendance. This comparative view would enable the hotel proprietors to plan in advance the seasonal problems and staff their systems more effectively. The benchmarking capability transforms untamed sentiment into an actionable intelligence on long term planning.

It also provides hotel specific deep view (FIGURE 8). For example, Hotel A10 shows the performance and business analysis granular drill-down that is shown by one hotel. Unlike broader seasonal and annual perspectives, this perspective of KPI allows restaurant owners to view not just macro-level data about your food safety, service and room comfort, but also to zoom in on individual service opportunities. The modeling will help the readers to find out the attributes of service that perform better than others and an area that requires urgent attention. As an example, by detecting leakages, the hotel (e.g. hotel A10) that has friendly staff but low room cleanliness can focus resources on housekeeping without making over-investment on areas with high performance. It is a selective method of increased efficiency and decision-making on a data basis.

6. USABILITY EVALUATION AND ANALYSIS

6.1 Evaluation Design

This visualization phase transformed the existing ABSA results into interactive dashboards to support informed decision-making by relevant stakeholders. We use usability evaluation [29, 30], method to assess the proposed dashboards for clarity, navigation, responsiveness, and relevance of the presented information.

6.2 Evaluation Methodology

Usability evaluation was performed by selecting the participants from different stakeholders and for this purpose we selected 10 potential hotel clients (n=10), 10 hotel owners/managers (n=10) and 05 website administrators or data analysts (n=5). All the participants were given different tasks to assess the usability of different parts of the dashboard. Each participant was given a questionnaire containing questions about their experience with the dashboard. A hybrid approach to evaluation was used to evaluate the dashboards in their entirety:

[label=•]

1. Quantitative Metrics: Task completion time, number of errors, and a five-point Likert scale survey measuring ease of use, clarity, and visual appeal.
2. Qualitative Feedback: Short semi-structured interviews to capture user impressions, preferences, and suggestions for improvement.
3. Video Observation Logs: Researcher notes and comments about the participants while they are interacting with the dashboard.

6.3 Stakeholder-Based Evaluation Results

6.3.1 Client dashboard

[label=•]

1. Task Performance: Clients completed assigned tasks with an average completion time of 1.8 minutes and an accuracy rate of 95%.
2. Satisfaction Scores: On a 5-point Likert scale, clients rated ease of use at 4.6, clarity of visuals at 4.7, and overall satisfaction at 4.5.
3. Notable Insight: 90% of participants reported that the dashboard improved their confidence in making booking decisions.

6.3.2 Website Owner dashboard

[label=●]

1. Task Performance: Website owners averaged 2.4 minutes per task with a 92
2. Satisfaction Scores: Participants rated usefulness of aggregated KPIs at 4.8, navigability at 4.4, and visual appeal at 4.3.
3. Key Finding: 80% of participants valued the consolidated sentiment distribution chart for identifying underperforming hotels.

6.3.3 Hotel Owner dashboard

[label=●]

1. Task Performance: Hotel owners/managers required more time due to data granularity, averaging 3.1 minutes per task with 89
2. Satisfaction Scores: Aspect-specific sentiment analysis received the highest rating (4.9), while dashboard responsiveness scored lower at 4.1, reflecting concerns about load times.
3. Behavioral Insight: 75% of owners indicated they would consider operational changes (e.g., staff training, housekeeping improvements) based on dashboard insights.

6.4 Quantitative Analysis

Across all three dashboards, several strengths were consistently highlighted:

1. Consistency in Visual Design – Uniform color schemes for sentiment categories enhanced recognition and reduced cognitive load.
2. Interactivity – The ability to drill down from aggregated statistics to individual review details increased user engagement.
3. Decision Support Value – 85% of participants confirmed that the presented insights could directly influence booking decisions, service improvements, or business strategies.

However, areas for improvement were also identified:

[label=●]

1. 40% of participants recommended hover-based tooltips to explain less familiar KPIs.
2. 25% of participants suggested optimizing dashboard load times, especially in the hotel owner's dashboard with its more granular data.

This usability evaluation (as shown in TABLE 4) demonstrates that the visualization dashboards effectively bridged the gap between complex ABSA outputs and real-world decision-making. The inclusion of quantitative measures and comparative results further validates the dashboards' reliability, providing stakeholders with actionable insights while identifying concrete areas for iterative improvement. Approximately 90% of clients reported increased confidence in booking decisions. Similarly, around 80% of website owners valued sentiment distribution visualizations, while 75% of hotel owners indicated that the system could support operational improvements.

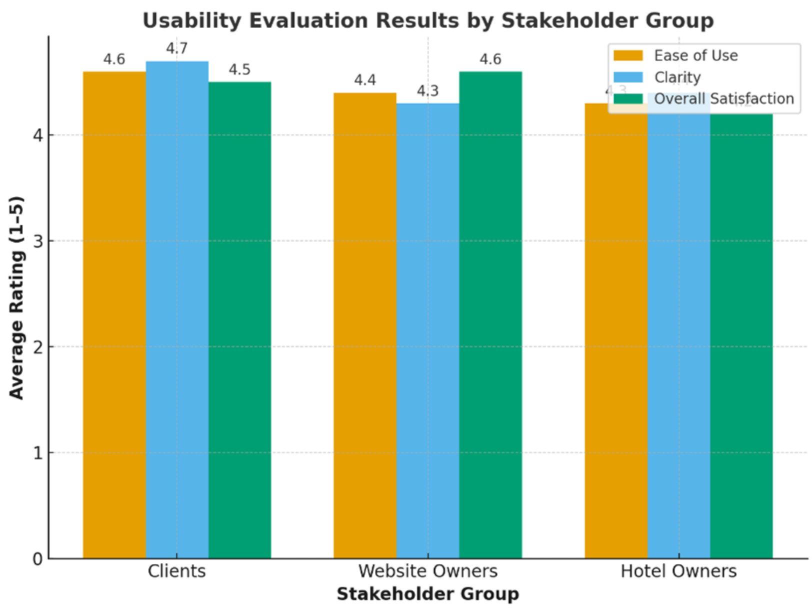

Figure 9: Usability ratings for Clients, Website Owners, and Hotel Owners.

In the graph shown in FIGURE 9, it's evident that clients reported the highest clarity scores, while Hotel Owners rated aspect-specific analysis highly but noted slower responsiveness. This visualization makes it easy to see at a glance how clients, website owners, and hotel owners rated their dashboards, reinforcing the quantitative findings.

As can be seen in the visualization of FIGURE 10, clients are the ones who performed the best in terms of accuracy in the shortest period of time, whereas Hotel Owners took a longer period of time to complete their tasks, however, with a high level of accuracy. This would complement the

Stakeholder Group	**Avg. Task Time**	**Accuracy Rate**	**Ease of Use**	**Clarity**	**Overall Satisfaction**
Clients (n=10)	1.8 min	95%	4.6	4.7	4.5
Website Owners (n=5)	2.4 min	92%	4.4	4.3	4.6
Hotel Owners (n=10)	3.1 min	89%	4.3	4.4	4.2

Table 4: Usability Evaluation Across Stakeholder Groups

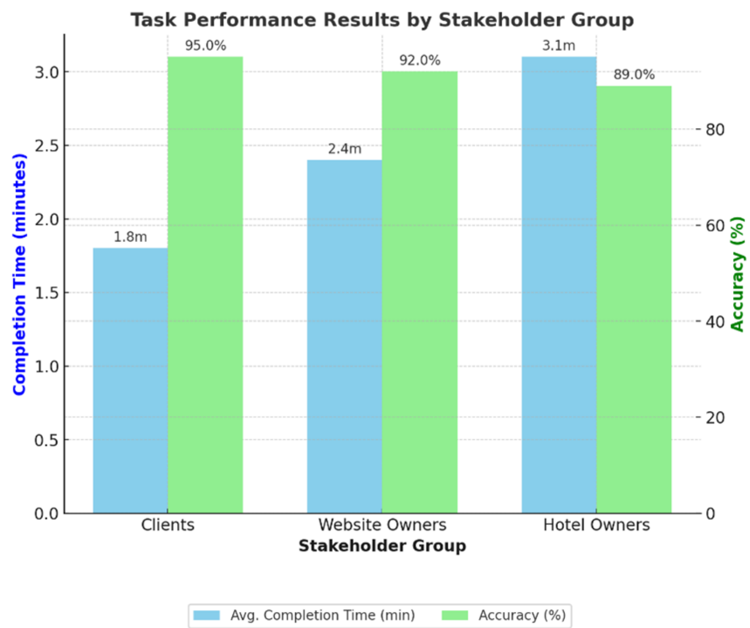

Figure 10: Task performance results for each stakeholder group.

previous chart of satisfaction ratings corresponding to the subjective rating of usability and objective performance of tasks.

7. CONCLUSION

The proposed work presents a semantic-aware aspect-based sentiment analysis framework that effectively addresses contextual ambiguity in customer reviews. The results of the analyses are integrated into interactive dashboards to transform sentiment data into strategic asset, which demonstrates that the model helps to fill the gap between theoretical studies and practice in business. By integrating word sense disambiguation with deep learning and graph-based techniques, the model is able to capture both contextual and structural relationships, resulting in improved aspect-level sentiment classification. The experimental results demonstrate that the proposed approach performs effectively and provides reliable outputs for decision support in the hospitality domain. In addition, the visualization module serves as an important component of the overall framework by ensuring the transition from computational analysis to actionable business intelligence. By utilizing the capabilities of Power BI, the system transforms raw sentiment analytics into dynamic and interactive stake-holder dashboards. The evaluation shows that the visualizations improve interpretability and stakeholder engagement, and also make decision-making more efficient. Overall, this visualization contributes to the practical value of the sentiment analysis in the hotel sector by improving visibility, benchmarking of their performance, and developing intervention.

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