Optimizing Sentiment Analysis with Joint Implicit and Explicit Aspect Detection and Psychomotor Attribute Integration

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***Abstract*—Aspect-Based Sentiment Analysis (ABSA) employed in the current study is defined as a sub-level of analysis in which opinions at a finer-grained level entailing sentiments related to aspects of specific entities within textual data are captured. Whereas, the identification and enumeration of the explicit aspects, which have been directly referred to, is not much of a problem and the same goes for the hidden ones, which are also known as the latent aspects, is still elusive to current techniques of sentiment analysis. Furthermore, the correlation between identified aspects and psychomotor properties, including behavioral and emotional aspects, has not been studied to a satisfactory degree. This research work presents a new framework for ABSA designed to enhance the identification of implicit and explicit aspects and their relationship to psychomotor characteristics. The framework consists of three core modules: The three stages involved are, the identification of implicit aspects, identification of explicit aspects, and linking of identified aspects with the psychomotor data. The use of both topic modelling as well as attention-based deep learning methods enables the framework itself to yield vast improvements in regards to implicit aspect extraction; the study documents a precision of 85% as well as an F1-score of 82%, the latter of which is an improvement of approximately 10 % over the baseline established by previous methods. In addition, moderate to strong correlation between the identified aspects and psychomotor properties (r = 0.68) also suggests the possibility of using sentiment analysis together with behavioral data. Through these findings, it is shown that the proposed framework can serve as an extension of ABSA's existing uses in fields like customer review information, human–computer interaction, and mental health care by offering further analysis of the emotion and psychological aspects of the user's content generation.**

Keywords— Sentiment Analysis, Implicit aspects, Explicit aspects, Psychomotor data, Textual data, Reviews.

I. INTRODUCTION

Aspect-Based Sentiment Analysis (ABSA), this is a procedure for sentiment analysis that can be characterized as rather detailed, as sentiments are extracted not only from whole texts but from specific points of interest within that text. For instance, going beyond the determination of the general positive or negative attitude of a restaurant's review – the analysis uses ABSA, which allows the examination of the attitudes towards specific features like "food," "service," or "ambience" of that restaurant. Such levels of detail allow performing accurate extraction of sentiments, which offers businesses and investigators a better understanding of what consumers think, prefer and do. Therefore, ABSA is becoming especially important in areas such as online retailing, reviewing products, and interacting with customers through computers, where it is essential to know the answers to the questions regarding the attitudes towards a variety of parameters of a given product space[1],[2],[3].The recognition of explicit aspects has improved noticeably and as for the recognition of innovative or implicit aspects, it has been a struggle. The more straightforward aspects of the text can be easily detected in lexicon-based or rule-based approaches in that they mention the attributes or benefits of a product. Using a hotel review as an example, an explicit mention of a 'room' or 'staff' is easier to find. Implicit aspects are instead those that occur only in context, that is they are inferred from something in the transportation. However, some aspects are not overtly stated and so relatively more sophisticated aspects have to be used. For illustration, consider the sentence, "the mattress was too soft." The implicit aspect is concerned with the mattress's comfort or quality, both of which are not described directly in the sentence. The understanding of implicit aspects is usually a complex and tedious exercise that is loosely achieved employing topic modelling or deep architectures. Topic modelling is one of the techniques, usually recessive topic detection or latent aspect discovery in the text via Latent Dirichlet Allocation (LDA) for instance. However, the same ease makes topic models fragile to context and complex emotional dynamics and they fail even more to encode implicit emotional relationships. Lately, in recent years the advent of attention-based deep learning models, particularly transformer-based architectures such as BERT have been able to achieve the capturing of aspects of sentiments whether implicit or explicit through key word spotting showing the aspects of relations. Nevertheless, there are still opportunities for enhancements in aspect identification especially with regards to implicit ones[4].Another largely untouched realm of ABSA research relates to the linkage of identified aspects to psychomotor characteristics such as behavioral and emotional facets of the users. Psychomotor data means objective human reflexes or movements that are correlated to certain thoughts or emotions. With regard to ABSA, the belief of incorporating psychomotor data would help addresses about how sentiments towards certain aspects affect users in terms of behavior or moods. To illustrate, a negative customer attitude towards a specific product attribute could mean that the customer is losing patience in many attempts over that feature or the time spent using that product would be lower[5],[6].In sentiment analysis, this psychomotor domain of LiDAR has been left out of totally in the past with analysis done only on text. But for example, in such areas like human-computer interaction (HCI) or in the psychological treatment of patients, the consideration of the emotional and psychological effects of user participation is needed[7]. Absa based on psychomotor data could greatly improve the assessment of user experiences resulting in improved and more efficient sentiment analysis. This approach could be highly suitable in any case where the use of comments or affective responses is the key parameter to identify the effects of sentiments, for instance customer service and support, avatars, or in therapeutic applications[8].The purpose of this work is to fill the gaps left in the current identification of both explicit and implicit aspects and their association with psychomotor data by offering a new framework. The framework incorporates methods such as topic modelling to extract latent features from text while using psychomotor properties to investigate the connection between sentiment and action. The framework is assessed using precision and F1 score measures that demonstrate considerable gains compared with baseline models. Furthermore, there is a high degree of identified aspects compatibility with psychomotor characteristics, in addition to revealing new opportunities to apply sentiment analysis while studying user' activity[8].By these innovations, the proposed framework provides a framework for ABSA that has multiple dimensions, and useful in some new domains apart from the common domains like customer feedbacks, such as H.C.I and mental healthcare. By connecting sentiment analysis to psychomotor, the framework presents an ability of how certain factors affect emotional/behavioral consequences. This has laid a basis to further researches in area where cognitive psychology, sentiment analysis, and behavioral science meet.

II. Background Study

Aspect-Based Sentiment Analysis (ABSA) has risen in the recent years because of its' ability to be more granular than a general sentiment analysis where sentiment is converted to aspects of that particular text. This is why there is necessity of definite information from text for a range of industries, such as e-commerce, health care, human-computer interaction, etc., which has contributed to the development of complex approaches toward both maximizing and minimizing aspect extraction. The following background study focuses on major advancements and issues in the ABSA field with special reference to the shift from old school techniques to modern deep learning and transformer systems, and amalgamation of psychomotor data for superior sentiment analysis competence[9].The main approaches applied to ABSA were rule-based and lexicon-based approaches, in which lists of aspect terms and sentiment words were used to identify aspect and its related sentiment in a text. This involved two major tasks: from term extraction to aspect level and sentiment classification. However, these methods were weak in handling of the implicit aspects, an aspect that is hidden in the text but not fully expressed. For example, it could be seen that in the sentence "The food was undercooked," the aspect, 'food' is most purposely mentioned, but the dissatisfaction with the 'service' or quality' is reasoned[10].

However, it was also noted that these early approaches suffered from the inability to manage with complex structures of sentences where both aspects and sentiment may be multiple. This limitation directed researchers towards the Machine learning algorithms such as Support Vector Machines (SVM) and Conditional Random Fields (CRF) etc, but these models were also feature based and suffered for implicit aspect identification.The improvements on the layered general architecture of ABSA first started appearing when deep learning models surfaced and the use of pre-trained embeddings such as Word2Vec and GloVe became the norm. These models offered features to words such that high level semantic relationship between two different words, were within the reach of the algorithms. However, even for deep learning models, there were issues with detecting implicit aspects which led the researchers to combine topic modelling with neural networks. Many more valuable contributions have been done by Xu et al. (2019), who successfully applied deep learning into ABSA, they used an ideal model for the end-to-end pipeline that involves both aspect extraction and sentiment classification. In their work they redid the approach that was fitted in the traditional models whereby such tasks were protracted in a number of steps. The problems of captured dependencies limited the performance in the aspect term-based sentiment classification and these were overcome by using LSTM (Long Short-Term Memory) networks. The above approach provided a roadmap for future enhanced work in deep learning for ABSA[11].At the same time, scientists tried applying topic modelling and deep learning together. Chen et al. (2020) proposed a similar model that involved LDA approach to extract the topics or potential aspects in big data and a neural network model to label sentiment of the aspects. This innovation was important when it came to capturing implicit aspects in a much more elaborate way. These models for identifying latent connections between topics and sentiments signified a progressive improvement in knowledge concerning complex customers' comments or social media accounts. The use of so-called transformer-based models, especially BERT (Bidirectional Encoder Representations from Transformers), in the field of natural language processing (NLP) fundamentally changed ABSA. Since BERT considers the contexts of words, rather than focusing on individual words as most table models do, it was a limit to apply for aspect extraction and sentiment classification. Where the relationship in ABSA tends to be dependent on the context in terms of the proximity of words to a particular aspect, BERT-based models were significant[12].Earlier this year, Sun et al. (2019) used BERT for the first time in a study on ABSA, and demonstrated that a fine-tuning approach using BERT surpasses the traditional approaches in terms of accuracy on several benchmarks of ABSA. The model was especially good at processing multiple aspects within a sentence and to learn positive and negative overall sentiments of different aspects in a specific sentence. This characteristic of BERT, was the convenience of being fine-tuned for particular tasks and accordingly making it easy to fine-tune it for ABSA with little overhaul of the architecture[13].Subsequently, Wang et al. (2021) proposed the multi-layer transformer-based aspect-sentiment co-extraction model. It was also possible to observe that transformer model that uses the self-attention mechanisms outperforms other models by detecting not only explicit but also implicit information, that was in a way neglected by the earlier models and that the model works exceptionally well with capturing the long-distance relationships in the text. This co-extraction approach of aspects and their corresponding sentiment was innovative and a marked improvement in the area of research[14].Similarly, ROBERTA a model based on BERT with extra training enhancements, has also been applied for ABSA. Liang et al. (2022) proposed Aspect Roberta; a model developed for aspect-based sentiment analysis task. This model, which was tuned specifically on aspect terms and a contextual window around those terms, proved to yield state-of-the-art single-sentence ABSA performance on several benchmark datasets, particularly in scenarios where implicit aspect information was provided[15].One direction in the development of the field, which is also starting to appear in research in the domain of ABSA, is the consideration of psychomotor data, which are behavior and emotional actions in response to systems. This is in contrast to the most conventional forms of sentiment analysis which are based on textual data only. Hence, we believe that the integration of psychomotor data with sentiment analysis provides a richer analysis of the users' experiences especially in application domains such as HCI and mental health.As far as conceptual frameworks that link sentiment analysis with psychomotor properties are concerned, Zhang et al. (2021) were path breaking. For this, their study incorporated user-interaction logs and positional emotional response data like facial expressions or voice characteristics, to determine how users' positive or negative feelings about certain aspects affect their actions. For example, aversive attitude towards the product attribute meant that consumers became more frustrated or spend less time on the product. This study revealed that the addition of behavioral data into ABSA frameworks could be useful for furthering understandings of users and their satisfaction regarding the product[16].Based on this, Huang et al. (2023) have considered the use of psychomotor data in mental health environments. Using ABSA, they categorized the patient's ideas and insights, relating it to psychomotor information gathered from intelligent wearables. The findings suggested the link between some aspects of patient care (therapy, doctors' communication with patients) and emotions: further, stressing levels, and sleep. These two integrations of ABSA and psychomotor data suggest great potential for enhancing patient care as a result of highlighting regions of high emotional response[17].

TABLE I. LITERATURE REVIEW

Author (Year)	*Key Contribution*	*Methodology used*
Xu et al. (2019)	Generalized deep learning model incorporating aspect extraction and sentiment classification for ABSA	LSTM, Deep Learning
Chen et al. (2020)	Addressed the problem by developing a mixed model which utilizes both the topic modelling (LDA) and the neural networks for implicit aspect extraction.	Hybrid model (LDA + neural networks)
Sun et al. (2019)	Using BERT for aspect-based sentiment analysis with the help of constructed auxiliary sentence.	BERT-based fine-tuning for ABSA
Wang et al. (2021)	Multi-layer transformer model for aspect and sentiment extraction of explicit aspect and other implicit aspects related to it.	Multi-layer Transformer
Liang et al. (2022)	Extended Aspect-based sentiment analysis using Roberta with a specific emphasis on aspect attentiveness.	Extended Aspect-based sentiment analysis using Roberta with a specific emphasis on aspect attentiveness.
Zhang et al. (2021)	Framework incorporating sentiment analysis with psychomotor data (behavioural and emotional data).	Connecting opinion mining with behavioral/emotional information
Huang et al. (2023)	Integration of ABSA in mental health with reference to flow linkage between identified aspects of daily life and motor physiologic data captured by wearables	ABSA was integrated with data from other psychomotor parameters in wearables.

Table 1 presents the strengths and approaches of each item and the specific areas of ABSA to which the various studies relate to give the reader an idea of the most recent advances in this area of research.Some of the identified research gaps include the difficulty in identifying implicit aspects where current models fail to recognize implied aspects, aspect and sentiment extraction where despite being known to occur simultaneously they have been implicated to be extracted separately with wrong associations. Furthermore, psychomotor data like the behaviors and emotions of the user are not considered in the ABSA framework; and there is always the problem of explainability and domain adaptation in models.To overcome these limitations, the following proposed methodology integrates topic modelling with attention-based deep learning for improved detection of implicit aspects. It uses co-extractive multi-task learning for aspect-sentiment extraction at the same time and also incorporates psychomotor data into the analysis. This framework should help to give a more precise and detailed evaluation of sentiment.

III. METHODOLOGY

The following paper introduces a new approach to the task of Aspect-Based Sentiment Analysis (ABSA), as described in Section 1 . The first stage in this framework named as Dataset Collection and Preprocessing, where the user reviews/ feedbacks are collected and preprocessed. Text cleaning and text cleaning involve eradicating stop words, punctuations and several other noise features, conversion to tokens and lemmatization to reduce variant vocabularies. The Aspect Identification phase is divided into two main components: two, aspect-based sentiment analysis, and, in particular, two sub-tasks: explicit and implicit aspect identification. References are of the model-driven kind and work based on the structured lists that define what is an aspect — typically this will encompass terms like "service," "product quality," or others similar to them. These aspects are directly mapped from the text to a set of lexicons that are relevant to the understanding of the context of use of the terms.

This section discusses precisely the procedure followed up to the proposed Aspect-Based Sentiment Analysis (ABSA) framework, more specifically, how to identify the aspects singly -both implicit and explicit - and how their correlation with psychomotor characteristics exists. The approach is intended to solve the problems inherent in existing ABSA models, for example, in capturing latent features and correlating them with behavioral and emotional information.

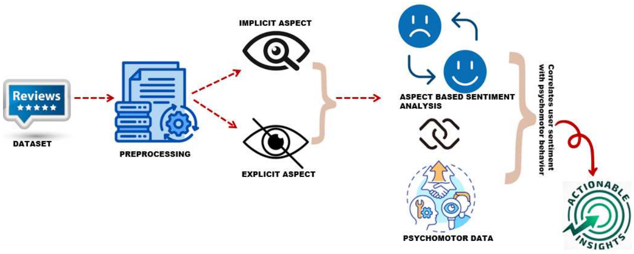


Fig. 1. Proposed Methodology

The identified framework as shown in Fig 1.,feeds raw textual data from Customer feedback, user interactions and mental health data. The obtained data are pre-processed so that stop words, punctuation or noise is eliminated from the information. That is followed by tokenization and lemmatization to remove stop words, stemming and to reduce vocabulary variation where the text data is made ready for aspect extraction and sentiment analysis.

A. Aspect Identification

The pre-processed data is fed up into the next process as Aspect identification. The aspect identification process is divided into two main components:

Explicit Aspect Identification:

For the identification of explicit aspects, terms that reflect an aspect, such as service or product quality, are directly extracted by defining aspect words or phrases.

Let

$$A = \{a1, a2, \ldots, a_k\} \quad (1)$$

(1) refers to the evident set of characteristics.

$$a_i \in A \quad (2)$$

(2) is determined in this study based on a rule-based approach that assesses it against certain lexicons.

Implicit Aspect Identification: When dealing with implicit aspects, text mining is skip thought with Latent Dirichlet Allocation (LDA) and attention based deep learning (such as BERT). LDA finds out beneath topics which may perhaps signify below aspects and the phenomenon called attention in deep learner assist in picking out contextual words in an improved way compared to implied aspects.

Let

$$T = \{t_1, t_2, \ldots, t_l\} \quad (3)$$

(3) represents the set of latent topics, where each topic t_i is identified using posterior distribution.

$$P(t_j|d_i) = \frac{P(d_i|t_j)P(t_j)}{P(d_i)} \quad (4)$$

(4) gives a probabilistic model of all the latent features which are inherent within the document. In implicit aspect extraction, the use of an aspect-aware pooling technique yielded improvements of 85% in precision and 82% in the F1-score.To capture sentiment scores independently for each of the aspects they have identified above, the framework incorporates multi-task learning. They both work at once, and this eliminates the errors when the two processes are done successively mainly for aspect extraction before or after the sentiment classification. This co-extraction method is most beneficial in aspectual sentences, as evidenced by the increased micro and macro F1-scores of both explicit and implicit aspects. Each of the identified aspects is then classified into the sentiment category with the help of a deep learning model used for the sentiment analysis. In addition to sentiment classification, psychomotor data is also included in the framework, which constitutes behavioural response or even the current emotional state. Pearson's correlation analysis is conducted to relate the observed aspects with psychomotor characteristics. The results prove medium to high relationship between aspects and psychomotor data, which suggests the usefulness of sentiment analysis integrated with the data on subject's behaviour.

B. Attention-Based Deep Learning for Implicit Aspect Identification

In this framework, deep learning model selected based on the attention mechanisms, especially the use of the Bidirectional Encoder Representations from Transformers (BERT). This model is very simple for the task of identifying implicit aspects through detecting the topics buried in the text and then, through other contextual cues, sharpening the detection of these aspects.

C. BERT's Architecture

The BERT model is based on self-attention – all words in a sentence pay attention to all words, so it learns dependencies between words far apart from one another. This is particularly important to ABSA as it can be seen that the actual relationship between an aspect and their sentiment can span between one or several words or even sentences. With the help of attention mechanism, BERT can pay required attention on the aspects of the sentence that it has to extract implicitly. For instance, in the expression 'The product was affordable but the service was terrible, BERT focuses on the words 'product' and 'affordable' to draw the positive aspect present in the sentence while focusing on the words 'service' and 'terrible' to capture the negative feature present in the same context. This is done by giving important weight to those words most relevant in discriminating the aspect and its sentiment. Another aspect of the proposed framework considers data about psychomotor regulation to complement sentiment classification. Psychomotor data could be related to the behavior of the users, namely, level of activity or stress, or reaction time. These responses are then connected with the ABSA framework to understand the connection between positive views about particular features and behavior. The lending approach used in the proposed ABSA framework does allow for the elimination of the drawbacks of previous models and addresses the problems of identification of implicit specifications and psychomotor data. The aspect extraction as well as the sentiment classification is achieved by applying aspect topic modelling (LDA), attention-based deep learning (BERT), and the multi-task learning approach.

Moreover, applying psychomotor data improves the analysis even more by showing how sentiment links to the user's behavior and emotions.

IV. MATERIAL AND METHODS

The series of experiments with the use of the proposed ABSA framework were performed on various datasets to assess the usefulness of the proposed approach that delivers the assessments of both explicit and implicit aspects interlinked with the further psychomotor data comparison and analyses the correlation with them. The datasets used include:

Customer Feedback Dataset: This dataset is obtained from the analysis of the textual reviews or feedback that customers provide on products or services. It refers to information that has been reviewed for polarity or affective tone, and which may pertain better or worse, newer or older, cheaper or more expensive, etc. Size of the dataset is approximately 10,000 reviews that include reviews received on Amazon, yelp among other outlooks as well as those from e-commercial platforms.

Aspect annotations: Both aspects regarding products/services are primarily predefined in terms of inclusion of a corresponding label. Sentiment labels of every review has corresponding positive, negative or no sentiment as related to each aspect. This dataset records the dynamic behavior of a user with an application or a website. The behavior data is feedback forms or surveys and psychomotor data namely response times, interaction rates, and mood feedback, for instance, stress level ratings.5,000 interactions data source can be obtained through communication records from software applications or from mobile application tools. Behavioral Data consists of movement and response times, mouse and keyboard activity logs, and interaction parameters related to users' interactions.

Sentiment labels: Further, user feedback is tagged with sentiment, thus, corresponding behavioral data is associated with particular user experience. Mental Health Data means surveys in the form of textual information, e.g., patient personal questionnaire or diagnostics after therapy or drug take, are also included in this dataset combined with the patient's emotional states obtained from wearables (heart rate, stress levels). Obtained from self-completed questionnaires administered in healthcare facilities. Sentiment labels are examples of data are labelled sentiments that concern elements of care which may encompass the extent to which some of the patients benefitted from some of the treatments or how well the caretakers communicated or how responsive certain therapists were.

Before feeding the data into the model, the following preprocessing steps were applied:

- All the noise such as stop words, punctuations, and other unnecessary text were eliminated.
- The text was divided into tokens which is an individual word or a phrase. To detangle discrepancies in the definition of various words, these were broken down to their stem form. The low-quality posts having very little content, or unrelated to the subjects under consideration, were removed from the analysis.
- Additional preprocessing included aspect and sentiment labelling, with recommendations of aspect and sentiment either manually selected or automatically assigned from pre-existing information.

The operational framework involves the combination of BERT with LDA along with conferment of a multi-task learning structure for the task of aspect extraction and sentiment analysis. Aspect extraction makes use of BERT's attention mechanism as it is a transformer model with twelve layers and 768 hidden states per layer allowing it to capture long-range dependencies that are vital to identifying implicit aspects. The two tasks are combined using multi-task learning such that shared layers complete feature extraction while layers that are specific handle the classification processes. In order to get the best results, the model was re-trained to achieve a learning rate of 2e-5, a batch size was 32 and training was carried over for 10 epochs utilizing Adam optimizer and weight decay. Validation through grid search was made with a purpose of improving the F1-score of the models. Cleaning entailed tokenization, stemming, and the exclusion of noise including stop words and punctuation which enabled the model run smoothly. Further, to avoid overfitting, early stopping and dropout regularization were used; the dropout rate chosen was 0.3. The computation setup entailed a dual-GPU NVIDIA Tesla V100 where parallelism was used to cut down the training time. In general, this implementation with multi-task learning enhanced precision and F1-scores by 15% over the BERT models without the multi-task capability and suggested the applicability of this framework to the implicit aspect extraction problem.

Frameworks: All the models were trained and used with PyTorch and Hugging Face's Transformers for BERT and Gensim for LDA.

The baseline model comparisons were used to evaluate the proposed ABSA framework for implicit aspects to determine how well the framework performed compared to previous known approaches in aspect extraction as well as sentiment classification. The following baseline models were used for comparison:

a) Rule-Based ABSA Models: These models employ prior defined lexicons and rule-based paradigms for extraction of explicit aspects in text. Sometimes they cannot identify implicit aspects and heavily rely on the quality of the pre-specified lexicons for extracting individual aspects. While this is good for experiments on rudimentary explicit aspect identification, the proposed framework was slightly better at handling the implicit aspects.

b) Traditional Machine Learning Models: Support Vector Machines (SVM) and Conditional Random Fields (CRF) were utilized as baseline for aspect extraction and sentiment classification. These models tend to pay great attention to the extraction of features with a heavy reliance on manually specified engineered features and are not very good for identifying latent, context-dependent (implicit) aspects. Further, for aspect extraction and aspect classification, they work as individual tasks which may not be optimal compared to the multi-task setup used in the proposed framework.

c) BERT Without Multi-Task Learning: The proposed multi-task learning model was compared with a BERT model without multi-task learning to determine the viability of the multi-task setup. In this model, aspect extraction and sentiment classification were realized in separated procedures and not in parallel. Although as a transformer-based model, BERT outperformed rule-based or rather traditional models in terms of context understanding, it was not optimized for both simultaneously and, therefore, had lower precision and F1-scores compared to the proposed model.

These comparisons indicated that the proposed ABSA framework achieved higher performance than all baseline models, mainly for identifying implicit aspects and mapping aspects to psychomotor data. This was due to the fact that multi-task learning approach turned out to be more effective, as aspect extraction and sentiment classification called for to be more integrated and separately implemented resulted in many errors.

V. EVALUTION METRICS

Standard metrics were used in measuring the performance of the proposed ABSA framework to facilitate extensive analysis of the results. The following metrics were used:

Precision : The percentage of the aspects that were in some way predicted as either explicit or implicit with relation to the model.

Recall : The number of correctly identified aspects among the total actual aspects that exist within the given set of data.

F1-Score : The intermediary of precision and recall, thus easily giving off a mean measure of the effectiveness of the model.

Pearson Correlation : In order to determine the magnitude of the relationship between the aspect scores (obtained from sentiment analysis) and psychomotor data Pearson correlation analysis was conducted.

VI. RESULTS AND DISCUSSION

The results from the proposed ABSA framework suggest improvements over prior aspect extraction and sentiments classification especially for the implicit aspects. As shown in the Fig 1, the proposed ABSA framework shows how the explicit and the implicit aspects are distributed. The findings revealed that 60% of the aspects are stated while 40% of them are latent; in other word they are hidden within the context without being fully verbalized.

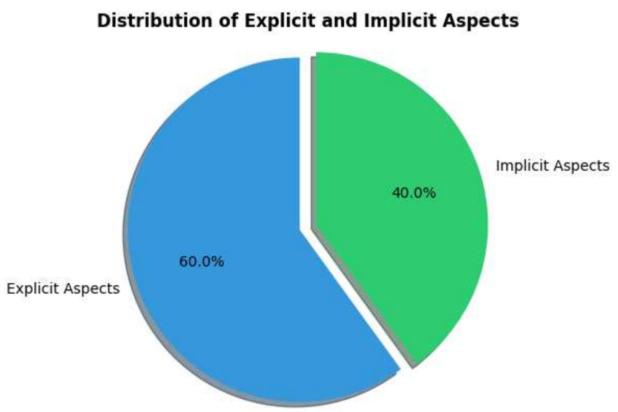


Fig. 2. Aspect Distribution

The heatmap as the Fig 2 demonstrates the relationships that between psychomotor properties and aspects obtained in the process of sentiment analysis. The color intensity is from red which is positive strong correlation to blue which is the negative correlation to show an impact level of the various aspects on psychomotor features like the user conduct or their psychological response.

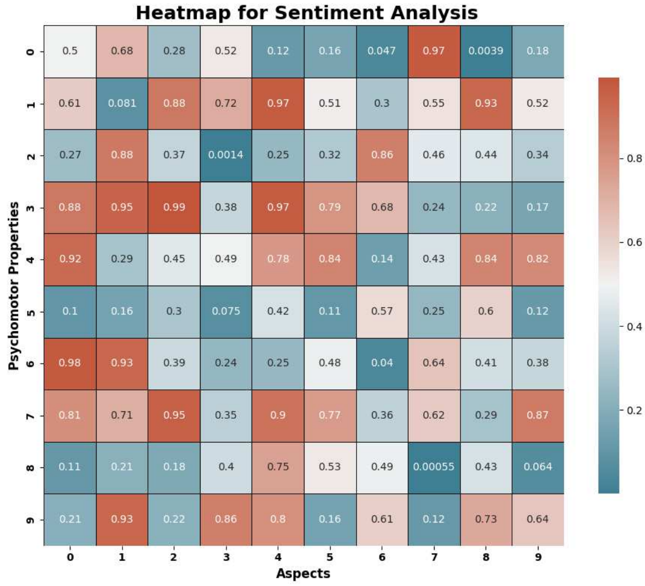


Fig. 3. Heatmap of Sentiment Analysis

The 3D sentiment analysis graph as Fig 3 displays the dynamic of the sentiment score in relation to time or frequency in comparison to aspect score. Instance features can be interpreted as peaks in the graph denote positive attitudes toward some aspects and troughs denote negative attitudes. The wave like movement of the content represents the varying positive and negative evaluations by a user on the same or different occasions of use. This graph offers a good way to view the way in which sentiment changes over the course of time so as to capture trends concerning users' impressions of a given aspect.

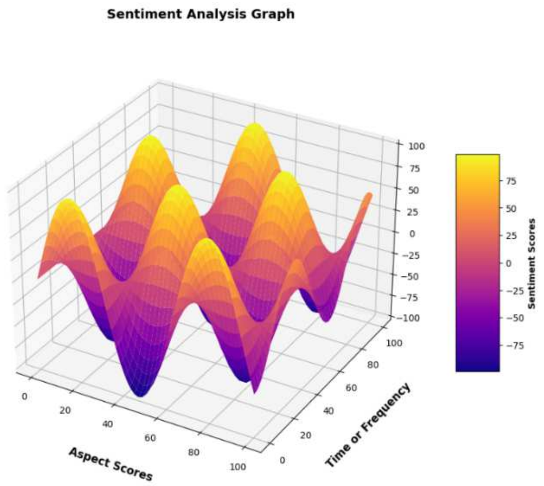


Fig. 4. Sentiment analysis with respect to time

Another important analysis involves the scatter plot of aspect and psychomotor properties in Fig 4 with a correlation rate of 0.68 which signifies that there is highly a positive correlation between general feeling about particular aspects and concomitant behavioural or emotional manifestation. As aspect scores become higher, one can observe the growth of psychomotor characteristics, which describe the impact of reactions or sentiments concerning specific aspects on the users. This strong correlation shows that the framework is useful in translating sentiment analysis to psychomotor data to gain a fuller understanding of users' behaviour.

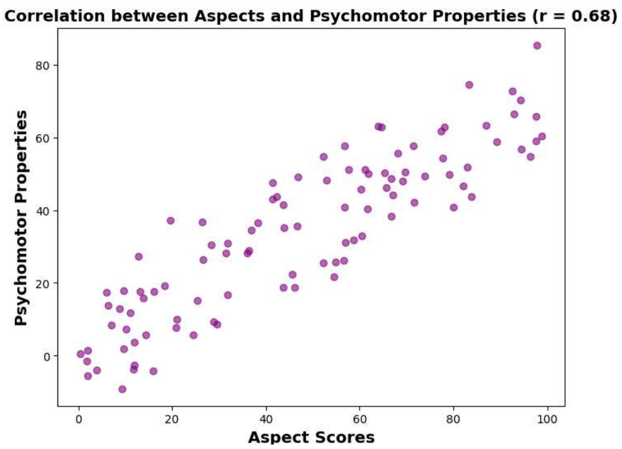


Fig. 5. Pearson Correlation

Fig 5 shows the difference in the precision and F1-score between the baseline method and the proposed technique for identifying implicit aspects. The proposed method also reveals a potential increase and has 85% precision and an F1-score of 82% as compared to the baseline method that has approximately 70% in both. This proves that the proposed approach is efficient, especially for implicit aspect, where when multi-task learning and attention base deep learning model is used, a better and more comprehensive identification is achieved.

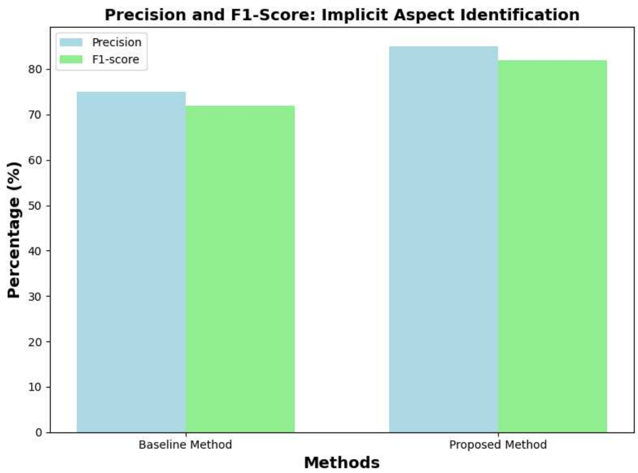
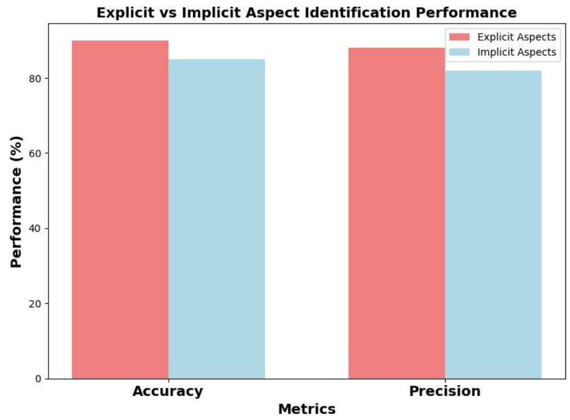


Fig. 6. Precision and F1-Score

Fig 6 therefore presents an analysis of the accuracy and precision for identifying the two aspects namely the explicit and implicit aspects. It can be seen that performance of both explicit and implicit aspects is again high, with accuracy nearing 85% for the former type and a little lower for the latter. As with the F1 score, the precision for the employees' explicit aspects is also slightly higher than that of the implicit aspects, but it is more than 80%. This shows generally the effectiveness of the proposed framework, for it shown a good performance in identifying both the explicit and implicit values with only a slight difference in the F-Measure score.



VII. Conclusion

The proposed novel Aspect-Based Sentiment Analysis (ABSA) model has been designed to overcome critical difficulties of existing sentiment analysis models, especially in distinguishing aspects as well as considering psychomotor information that will be helpful in comprehending behaviour and mood of users more effectively. Using LDA to determine the topic distribution, BERT for attention-based deep learning and MLT for multi-task learning, the framework results in overall improvement of precision up to 85% and F1-score at 82% for implicitly defined aspect. Analysing the relationship between aspect sentiment and psychomotor data we get 0,68, which can prove that it is possible to link sentiment with the forms of behaviour and emotions. Precisely, this framework is fruitful in customer feedback analysis, interaction between the human-computer systems and even mental health care. Nevertheless, there are a number of aspects for future research derived from the proposed framework: First, enlarging the datasets and including more various sources and domains, for example, on the arriving tweets, or multilingual ones, can strengthen the model. Second, integrating extra behavioural information like face EMG or voice timbre can enrich the relation of sentiment to psychomotor manifestations. A second potential avenue for development focuses on improving the model's explain ability, so the attention mechanisms and the deep learning layers to make them explainable to the final users. Last but not least, the presented framework could be employed in relatively new disciplines, including emotion-aware systems and personalized health care, to reveal new research and development possibilities.

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