Opinion Mining for Educational Data-driven Decision-making in Computing-supported Interventions for Children with Autism

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Abstract—**Parental feedback regarding interventions at autism therapy centres is increasingly accessible via online platforms. However, it remains predominantly qualitative and underutilised in data-driven educational decision-making environments. To bridge this gap, the present study introduces an opinion mining framework that could convert unstructured parental testimonials into actionable insights to inform computer-supported interventions for children with autism spectrum disorder. The principal aim of this research was to scrutinise parental feedback for emergent thematic patterns and sentiment trends capable of guiding evidence-based educational and therapeutic strategies. By employing purposive sampling, 118 testimonials were gathered from Google Reviews and Telegram channels spanning from July 2024 to October 2025, encompassing both textual and image-based contents. The Optical Character Recognition (OCR) software was utilised to extract texts from images, followed by conventional preprocessing. Latent Dirichlet Allocation (LDA) and Aspect-Based Sentiment Analysis (ABSA) facilitated thematic extraction and aspect-specific sentiment appraisal, with the application of a logistic regression model for sentiment classification. The analysis discerned five prevalent themes, namely progress, behaviour, routine, communication, and school interaction, with 81.4% of feedback evincing positive sentiments, which were particularly pronounced in the learning, behaviour, and speech domains. The sentiment classifier registered 83% accuracy alongside an F1-score of 0.91 for positive sentiments. These outcomes affirmed the efficacy of opinion mining in advancing data-informed educational decision-making processes and perpetual refinement within autism-focused therapeutic and educational paradigms.**

Keywords—**opinion mining, sentiment analysis, OCR, autism intervention, Latent Dirichlet Allocation (LDA), Aspect-Based Sentiment Analysis (ABSA), topic modelling, data-informed education**

I. Introduction

The increasing prevalence of Autism Spectrum Disorder (ASD) necessitates effective therapeutic interventions, yet understanding parental perspectives on these services remains a crucial, underexplored area for optimising outcomes and informing educational practices [1]. Opinion mining, also known as sentiment analysis, offers a robust methodological framework for extracting and interpreting nuanced parental opinions from unstructured textual data. It is a powerful tool for extracting subjective information from this type of data, which could provide a deeper understanding of sentiments. This interdisciplinary technique leverages machine learning, Natural Language Processing (NLP), sociology, and psychology to discern emotional tones and opinions from unstructured texts [2].

In the educational context, opinion mining has been widely adopted to process feedback from students for enhancing pedagogical strategies and improving learning and teaching practices [2]. This approach has helped characterise interactions between students and teachers that could provide timely, personalised feedback [3]. Previous studies have systematically classified the application of NLP, deep learning, and machine learning solutions for sentiment analysis in education, primarily focusing on student feedback within learning platforms [4]. This continuous analysis of students' opinions could help in making data-informed decisions and evaluating educational procedures [5]. However, the application of opinion mining to parental feedback on autism interventions, particularly in the context of therapy centres, is less common despite its potential of providing invaluable insights for improving therapeutic efficacy and educational integration [6]. This research aimed to address this gap by applying advanced sentiment analysis techniques to systematically analyse parental feedback regarding autism interventions by therapy centres, thereby contributing to data-driven improvements in both therapeutic approaches and educational support for children with ASD.

II. Literature Review

ASD is a complex neurodevelopmental condition characterised by challenges in communication, social interaction, and repetitive behaviours [7, 8]. Early diagnosis is paramount to enable timely therapeutic interventions that could foster development and improve outcomes in several areas, such as communication, social interaction, and cognitive skills [8–10]. While interventions like the Applied Behaviour Analysis are widely used, the increasing number of ASD cases highlights different challenges, including the

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limited availability of licensed practitioners and the need for data-driven decision-making in treatment planning [11]. Parental involvement in the intervention process has consistently been shown to be crucial for achieving positive outcomes, with studies demonstrating that early, parent-mediated interventions significantly reduced symptom severity and improved their child's developmental trajectories [12–15].

Opinion mining, interchangeably known as sentiment analysis, involves programmatically converting texts into structured data by categorising words as either positive or negative using sentiment dictionaries, and by performing analyses at various levels, such as documents, sentences, and aspects [2, 16, 17]. Recent advancements in Artificial Intelligence (AI) technologies, such as machine learning, deep learning, and transformer models like Bidirectional Encoder Representations from Transformers (BERT) and ChatGPT, have significantly enhanced the accuracy and automation of sentiment analysis, particularly for processing complex textual data, including parental dialogues for early ASD detection [11, 18].

Opinion mining has been widely adopted in the educational context to process feedback from students, which would subsequently be used to enhance pedagogical strategies and improve learning and teaching practices [2]. This approach could help characterise interactions between students and teachers, and subsequently, provide timely, personalised feedback [3]. Systematic reviews have classified the application of NLP, deep learning, and machine learning solutions for sentiment analysis in education as primarily focusing on student feedback within learning platforms [4]. This continuous analysis of the opinions of students could assist in making data-informed decisions and in evaluating educational procedures [5, 7]. Beyond student feedback, opinion mining may also include parental feedback within special education. For instance, studies have explored text mining and sentiment analysis on media platforms like Reddit to understand the experiences of parents and teachers in special education [19–21].

Parents of children with ASD frequently encounter significant challenges, including financial burdens, social issues, and difficulties navigating support systems [22–25]. Understanding their experiences could further enrich the knowledge into the complex interplay between autism, parenthood, and service provision [26, 27]. Previous studies have also emphasised on the importance of including the perspectives of parents and caregivers of autistic young people to inform future intervention development [28, 29].

Opinion mining has revealed that while parental feedback may indicate positive experiences with interventions, certain domains present persistent challenges. For instance, the analysis of forum posts from autism message boards showed that parents would often evaluate the benefits versus burdens of services [1]. Notably, domains like social interaction and sleep often require enhanced therapeutic attention due to ongoing difficulties. Sleep disturbances, for example, are a prominent co-occurring issue among children with ASD, with alterations impacting cognitive and behavioural outcomes [30, 31]. These nuanced insights are crucial for tailoring interventions to address specific needs across different cognitive, social, and linguistic abilities [32–34].

Opinion mining and sentiment analysis are increasingly vital for data-driven decision-making in education, which would enable evidence-informed improvements in teaching, learning, and interventions for individuals with ASD. By streamlining feedback collection, interpretation, and application, these techniques have facilitated the optimisation of autism intervention programmes within educational settings. This study has also demonstrated how parental feedback could be systematically analysed to transform their lived experiences into actionable insights. This knowledge could empower educators and therapists to refine their instructional strategies, bolster inclusive practices, and align therapeutic interventions with measurable learning outcomes.

III. Methodology

A. Research Design

This section details the research design employed in this study to accomplish the objectives, specifically the analysis of parental feedback concerning autism interventions at therapy centres using opinion mining and sentiment classification. A quantitative text analytics methodology was utilised to systematically extract, process, and interpret insights derived from parental testimonies. The overarching methodological framework encompasses five sequential stages, namely data collection, text preprocessing, opinion mining and thematic analysis, sentiment classification, and model evaluation, as depicted in Fig. 1.

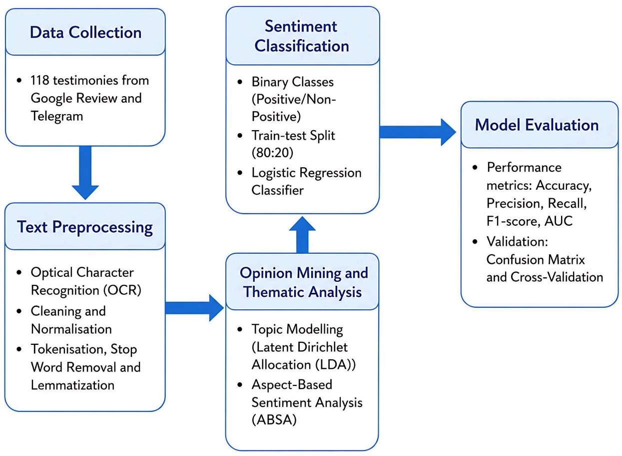

Fig. 1. Methodological framework.

B. Data Collection

A corpus comprising 118 parental testimonies was compiled, sourced from two primary platforms, namely Google Reviews (n = 30) and dedicated Telegram feedback channels (n = 88) associated with a therapeutic institution. The dataset encompassed the period spanning from July 2024 to October 2025. Each submission expressed parental perceptions regarding their child's developmental trajectory following therapeutic interventions. Fig. 2 presents representative examples of these testimonies, as derived from both Google Review and Telegram sources. In adherence to ethical guidelines and to ensure privacy, only publicly accessible and sufficiently anonymised data were incorporated. The integrity of the dataset was preserved by systematically excluding redundant entries, promotional content, and incomplete statements.

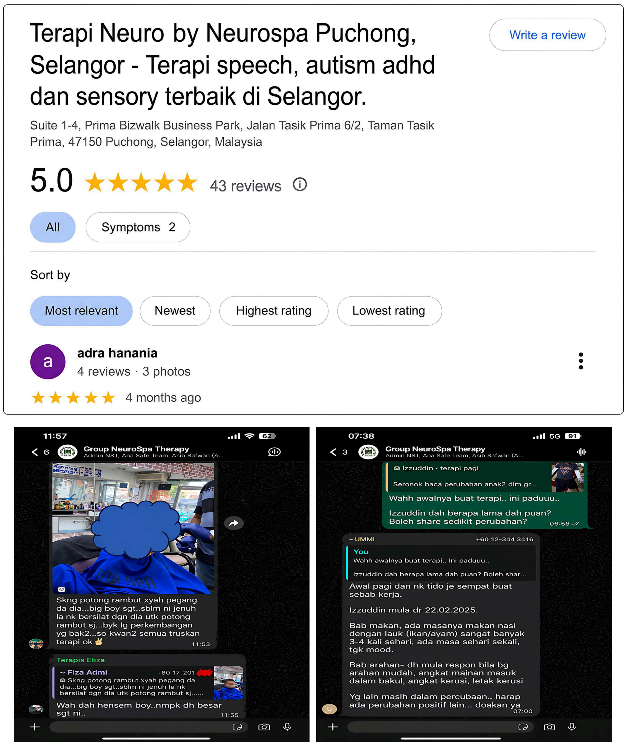

Fig. 2. Representative samples of parental testimonies sourced from Google review and telegram.

C. Text Preprocessing

Prior to analysis, the textual dataset was subjected to a rigorous preprocessing pipeline designed to guarantee clarity, uniformity, and analytical robustness. Image-based parental testimonials were initially transcribed into machine-readable texts using the Optical Character Recognition (OCR) software. The resultant texts underwent normalisation through lowercasing, and elimination of punctuations, emojis, and superfluous whitespace. Tokenisation was subsequently employed to divide these texts into discrete lexical units, accompanied by stop word removal and lemmatisation to convert words into their canonical forms, thereby establishing a standardised corpus for subsequent analyses.

To enable numerical encoding, these preprocessed texts were vectorised using the Term Frequency-Inverse Document Frequency (TF-IDF) technique. This technique accorded higher prominence to distinctive terms that appeared frequently in individual testimonials, yet infrequently across the entire corpus, thereby augmenting the responsiveness of downstream topic modelling and sentiment analysis to prominent semantic attributes. Fig. 3 depicts a representative exemplar of parental testimonials in their original and translated iterations.

Id	Source	Text_clean	Text_clean_English	Text_clean_English_processed
1	Telegram	alhamdulillah tant	praise be to god, th	praise god tantrum reduce go crowded place child control emotion
2	Telegram	alhamdulillah sele	praise be to god, af	praise god therapy many change child focus understand instruction fast
3	Telegram	alhamdulillah untu	praise be to god, fo	praise god adam naufal progress term communication interaction
4	Telegram	selepas terapi Ahr	after therapy, ahma	therapy ahmad hold pencil write assistance
5	Telegram	isu menulis di sek	the writing issue at	writing issue school child write slow home writing speed improve
6	Telegram	dulu suka menjeri	previously loved to	previously love scream calm control emotion better
7	Telegram	alhamdulillah suda	praise be to god, ha	praise god start learn share toy younger sibling
8	Telegram	selepas beberapa	after several sessio	several session child say new word week
9	Telegram	anak semakin suk	the child increasingl	child increase like eat vegetable try new food
10	Telegram	waktu tidur lebih t	sleeping time is mo	sleep time regular stay late night

Fig. 3. A sample of translated and preprocessed parental feedback.

D. Opinion Mining Techniques and Thematic Analysis

Subsequent to the text preprocessing phase, this research progressed into the opinion mining and thematic analysis phase. This phase was designed to unveil latent themes and discern sentiment patterns within the collected parental testimonies. This phase involved the application of two complementary analytical methodologies, namely Topic Modelling and Aspect-Based Sentiment Analysis (ABSA). Specifically, the Topic Modelling component leveraged the Latent Dirichlet Allocation (LDA) algorithm to discern recurring word clusters and reveal underlying thematic structures in the dataset. This step allowed for the systematic extraction of overarching themes, thus revealing the primary subjects and concerns articulated by parents regarding interventions at the autism therapy centre [9].

1) Latent Dirichlet Allocation (LDA)

The LDA algorithm was used to identify underlying themes in the processed parental testimonies. Each document was treated as a mixture of topics and defined by a probability distribution of words. This model detected latent patterns by analysing word co-occurrences across the corpus. Prior to modelling, the selected text was transformed using Term Frequency-Inverse Document Frequency (TF-IDF), which measured the importance of words relative to their frequency in the entire dataset. This weighting ensured that distinctive, topic-defining terms could have greater influence on the model.

The LDA algorithm was configured to yield five topics, as determined through iterative experimentation to enhance interpretability and topic coherence. Topic selection emphasised semantic clarity and congruence with developmental domains pertinent to autism interventions, rather than exclusive dependence on optimisation metrics. The TF-IDF vectorisation was utilised to foreground discriminative terms, thereby diminishing the prominence of prevalent yet less informative vocabulary. The emergent topics were interpreted by scrutinising leading keywords and their contextual deployment in the parental testimonials, thus permitting apt thematic nomenclature.

The operationalisation of the LDA algorithm additionally mandates a predefined quantity of topics, a comprehensive lexical dictionary, and the preprocessed corpus as indispensable inputs, as shown in Algorithm 1. This configuration enabled the discernment of semantically coherent topics that encapsulated recurrent parental concerns and observations, including learning progress, behavioural adaptation, and routine management. This methodological framework, thereby facilitated the strategic prioritisation of discriminative vocabulary, consequently augmenting the efficacy of the LDA model in revealing salient topics [10].

Algorithm 1. Algorithm of Latent Dirichlet Allocation (LDA)

Input: *Preprocessed text corpus D*
Output: *Topic-word distribution β, Document-topic distribution θ*

0. **START**
1. Vectorise D using TF–IDF ($max\_df = 0.95$, $min\_df = 2$)
2. Initialise LDA parameters:
   number_of_topics = 5
   α = Dirichlet prior for document-topic distribution
   β = Dirichlet prior for topic-word distribution
3. For each document d in D:
   Sample topic distribution $\theta\_d \sim Dir(\alpha)$
   For each word w in d:

Sample topic z ~ Mult(θ_d)
Sample word w ~ Mult(β_z)
4. Train model using iterative EM optimisation
5. Extract top-k words per topic based on *β_z*
6. Label and interpret topics
7. **END**

2) Aspect-Based Sentiment Analysis (ABSA)

To complement topic modelling, ABSA was employed to quantitatively assess parental sentiments regarding specific developmental domains. While the LDA served to identify underlying thematic structures, ABSA facilitated a more granular evaluation by assigning sentiment polarity scores to predefined aspects for each testimonial. This methodological approach enabled an analysis that transcended mere overall sentiment trends, thereby pinpointing areas of satisfaction or concern within distinct facets of therapeutic outcomes. Likewise, ABSA facilitated granular sentiment assessment by associating predefined developmental domains with curated keyword collections, thereby enabling the examination of sentiment polarity at the aspect-specific level rather than at the document level.

The aspect dictionary was developed through an iterative methodology that integrated developmental domains derived from the literature with empirical analysis of prevalent terms in the dataset. For instance, keywords, such as "reading," "learning," and "academic progress" were mapped to the Learning/Academic aspect, whereas terms, such as "tantrum," "focus," and "attention" were associated with the Behaviour aspect. Keywords were validated against autism intervention literature and reviewed by researchers with experience in educational technology and autism-related studies. The validation process was further supported by conducting domain-informed validation to ensure the semantic appropriateness and contextual relevance of keyword-to-aspect assignments. To address ambiguity and polysemy, contextual co-occurrences were analysed, with overlapping keywords conservatively assigned to primary aspects. Testimonials encompassing multiple aspects underwent systematic disaggregation to enable precise sentiment aggregation for each developmental domain, thereby averting the conflation of sentiment scores across distinct aspects.

This step was executed in Python 3.10, utilising Pandas for textual data manipulation and NumPy for numerical computations. Following the mapping of keywords to their respective aspects, entries encompassing multiple aspects were disaggregated into individual rows, and the mean sentiment score for each aspect was subsequently computed. To enable comparative analysis across different aspects, scores were transformed into percentages using the following formula: (average score/2) × 100. The divisor '2' signifies the maximum attainable sentiment value, rather than the total number of sentiment categories, thereby ensuring a consistent proportional conversion within a 0%–100% scale, as shown in Algorithm 2.

Algorithm 2. Aspect-Based Sentiment Analysis (ABSA) algorithm

Input: List of testimonial texts (cleaned and translated), sentiment score for each
Output: Table of aspects with *count* and *average sentiment*

0. **START**
1. Define Aspect Dictionary:
   Create a mapping of each aspect to its keyword list
   e.g. "Sleep" → ["sleep", "tired", "malam", "rehat"]
2. Assign Aspects to Each Text:
   For each text in dataset:
   For each aspect in Aspect Dictionary:
   If any keyword for that aspect is found in text:
   Tag that aspect to the text
3. Create Aspect Table: Expand multi-aspect entries so each aspect occupies a separate row
4. Calculate Sentiment Per Aspect: Group data by aspect
   Compute: *Count of occurrences, Average sentiment score (0 = negative, 1 = neutral, 2 = positive), Sentiment percentage = (average score / 2) × 100*
   Return: Table showing *aspect*, *frequency*, and *mean sentiment percentage*
5. **END**

E. Sentiment Classification Model

A sentiment classification model was formulated to enable the automated assignment of parental feedback to binary sentiment categories, which functioned as the predictive module within the proposed opinion mining framework. To counteract class imbalance and augment classification robustness, the original sentiment labels, namely positive, neutral, and negative were recast into a binary classification paradigm. Positive sentiments were designated as class '1', whereas neutral and negative sentiments were amalgamated into class '0'. This rule-based binarization strategy upholds the core distinction between satisfaction and dissatisfaction, while ameliorating the skewness attributable to the paucity of negative instances, as shown in Algorithm 3.

Algorithm 3. Algorithm of sentiment classification model

Input: Preprocessed testimonial texts with sentiment labels
Output: Binary sentiment predictions *(positive = 1, non-positive = 0)*

0. **START**
1. Convert sentiment labels:
   Positive (2) → 1
   Neutral (1) and Negative (0) → 0
2. Vectorise translated text using *TF-IDF*
3. Train Logistic Regression Classifier:
   model = LogisticRegression()
   model.fit(X_train, y_train)
4. Evaluate model using 5-fold cross-validation:
   scores = cross_val_score(model, X, y, cv=10)
5. **END**

The translated and preprocessed textual data were numerically vectorised using the TF-IDF technique. This method assigned weighted values to terms, prioritising those with high frequency within specific documents but low occurrence across the overall corpus, thereby optimising the model's capacity for discrimination [35]. Next, a logistic regression classifier was implemented and trained in a Python 3.10 environment, utilising the scikit-learn library. Logistic regression was chosen for its interpretability, computational efficiency, and appropriateness for binary classification on small- to medium-scale datasets. In contrast to more complex models that necessitate large volumes of training data, this classifier delivers transparent decision boundaries and consistent performance under data scarcity. These traits are especially valuable in educational and therapeutic domains where explainability fosters stakeholder trust and promotes model adoption. The dataset was systematically divided into separate training and testing subsets. Rigorous model evaluation was performed via 10-fold cross-validation to ensure robust performance, mitigate potential overfitting, and confirm generalisability across varied data splits.

To address the inherent class imbalance within the dataset, several corrective strategies were considered during model development. However, advanced resampling techniques, such as the Synthetic Minority Oversampling Technique (SMOTE) or cost-sensitive learning approaches, were not implemented due to the relatively small dataset size (n = 118), which may introduce synthetic noise and reduce model generalisability. Oversampling in limited textual datasets could artificially replicate or generate minority instances that do not adequately capture the true linguistic variability of the data, potentially leading to overfitting and unstable decision boundaries. This effect would particularly be pronounced when minority class samples are sparse and heterogeneous, since synthetic augmentation may distort the underlying data distribution rather than enhance it.

Instead, the present study prioritised model interpretability and stability by employing a logistic regression classifier with stratified data splitting and cross-validation. This approach ensured that the evaluation remained reflective of the true data distribution. Furthermore, the binary classification strategy was adopted to partially mitigate class imbalance while preserving the distinction between positive and non-positive sentiments. This methodological choice aligned with exploratory analytical objectives, where the emphasis was placed on identifying dominant sentiment patterns rather than achieving fully balanced classification performance.

F. Model Evaluation

This methodological framework culminated in a rigorous evaluation of the sentiment classification model, aimed at ascertaining its reliability, stability, and predictive capabilities. To quantitatively assess the efficacy of the model in discerning sentiment polarity within parental testimonies, a suite of performance metrics was judiciously employed. Specifically, these metrics encompassed Accuracy, Precision, Recall, F1-score, and the Area Under the Receiver Operating Characteristic Curve (AUC). Collectively, these indicators have furnished a comprehensive, multidimensional assessment of the proficiency of the model in differentiating between positive and non-positive sentiments, as shown in Algorithm 4.

Algorithm 4. Model evaluation procedure

Input: Trained Logistic Regression model, test data
Output: *Accuracy, Precision, Recall, F1-score, AUC*

```
0. START
1. Predict labels: y_pred = model.predict(X_test)
2. Compute metrics:
     accuracy = accuracy_score(y_test, y_pred)
     precision = precision_score(y_test, y_pred)
     recall    = recall_score(y_test, y_pred)
     f1        = f1_score(y_test, y_pred)
3. Compute AUC:
     y_prob = model.predict_proba(X_test)[:,1]
     auc = roc_auc_score(y_test, y_prob)
4. Perform 10-fold cross-validation:
     scores = cross_val_score(model, X, y, cv=10)
5. Generate confusion matrix:
     cm = confusion_matrix(y_test, y_pred)
6. END
```

IV. Results

A. Overall Sentiment Distribution

The overall sentiment distribution, derived from 118 parental testimonies, is presented in Table 1 and visually represented in Fig. 4. Parental feedback was categorised into three distinct classes, namely positive, neutral, and negative to effectively capture the emotional polarity expressed in these responses. Specifically, 96 testimonies indicated positive sentiments, 14 were classified as neutral, and 8 conveyed negative sentiments. Table 1 and Fig. 4 reveal a sentiment distribution that is strongly skewed towards positive feedback, wherein 81.4% of the testimonials have been classified as positive, signifying substantial parental satisfaction with the interventions at the therapy centre. Telegram emerged as the primary source of feedback, contributing 88 testimonies, whereas Google Reviews provided 30. A consistently positive tone was observed across both platforms, further reinforcing the prevalence of favourable parental experiences. Positive feedback frequently highlighted tangible improvements, such as visible developmental progress, enhanced attention spans, and improved emotional regulation among the treated children. Neutral feedback commonly presented mixed evaluations by recognising existing progress, while simultaneously proposing areas for further enhancement. In contrast, negative feedback that constituted 6.8% of the dataset predominantly highlighted concerns over therapy session frequency and perceived delays in developmental progress, as opposed to intrinsic dissatisfaction with intervention quality. The associated pie chart in Fig. 4 clearly illustrates a skewed sentiment distribution characterised by an overwhelming dominance of positive opinions. These results supported the interpretation that parental perceptions of services offered by the therapy centre were largely favourable within the analysed dataset.

Table 1. Sentiment class distribution

Source	Negative	Neutral	Positive
Google Review	1	5	24
Telegram	7	9	72
Total	8 (6.8%)	14 (11.9%)	96 (81.4%)

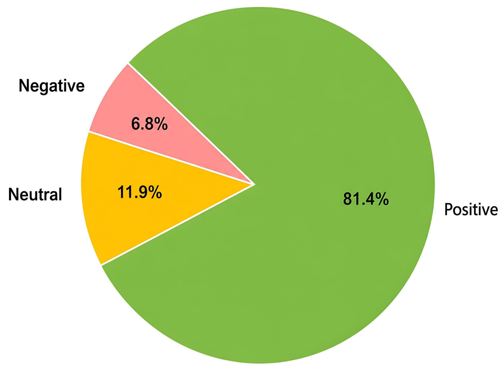

Fig. 4. Sentiment distribution.

B. Dataset Preparation for Classification

Following the sentiment distribution analysis, the dataset was prepared for subsequent model training and evaluation. Each parental testimony was subjected to preprocessing techniques involving the removal of superfluous symbols, normalisation of case formatting, and elimination of stop words to ensure a refined textual input. Subsequent to this data cleaning phase, the corpus is systematically partitioned into distinct training and testing subsets, as delineated in Table 2. The training set comprised 94 samples, while the testing set consisted of 24 samples. This stratified division was meticulously executed to uphold proportional representation of sentiment classes, thereby facilitating consistent model learning and an impartial evaluation of performance. This separation was intentionally structured to mitigate the risk of overfitting and to foster generalisability to previously unobserved data, which is a critical consideration in sentiment analysis tasks characterised by natural language variability.

Table 2. Testing set and training set

Dataset Portion	Positive	Non-Positive
Full Dataset	96	22
Testing Set (20%)	20	4
Training Set (80%)	76	18

To mitigate the challenge of class imbalance, a binary classification framework was implemented to consolidate neutral and negative sentiments into a singular ‘non-positive’ category. This re-categorisation not only streamlined the predictive task but also maintained the crucial distinction between expressions of parental satisfaction and those indicative of concern. As illustrated in Table 2, this strategic transformation yields a more manageable dataset, thereby improving model interpretability, while rigorously preserving the inherent emotional polarity within the textual corpus. This methodological adjustment was critical for enabling the classifier to accurately differentiate between genuinely positive parental experiences and those conveying reservations or dissatisfaction.

C. Word Frequency and Textual Trends

Subsequently, the analysis concentrated on investigating word frequency distributions to discern prominent themes within the collected parental testimonials. Fig. 5 illustrates a word cloud as a complementary visual tool integrated with the subsequent analytical findings to provide an intuitive overview of the dominant lexical patterns prior to detailed algorithmic analysis. This word cloud was generated from the complete corpus of parental testimonials by incorporating testimonials across all sentiment categories to delineate overarching lexical trends and recurrent themes throughout the dataset rather than sentiment-specific subsets. This visualisation delineated the most prevalent lexical items throughout the dataset. Lexical units, such as ‘child,’ ‘change,’ ‘now,’ ‘sleep,’ ‘eat,’ and ‘day’ were observed with high frequencies, which may correspond to the thematic areas later identified through topic modelling, particularly those related to daily routines and behavioural patterns.

The occurrence of terms like ‘clever,’ ‘focus,’ and ‘positive’ may be associated with a prevailing sense of optimism and perceived developmental enhancement, whereas infrequent mentions of ‘night,’ ‘tantrum,’ or ‘afraid’ may indicate latent concerns associated with emotional self-regulation and sensory processing. These lexical patterns were consistent with the sentiment classification results, where a predominance of positive opinions was observed, thereby reinforcing the identified sentiment trends. Therefore, the word cloud represented a supportive visualisation that could complement the findings from topic modelling and sentiment analysis, rather than as an independent analytical outcome. This extensive lexical examination may provide initial insights into recurrent behavioural facets reported by parents, thus establishing a substantive basis for subsequent topic modelling and granular aspect-based sentiment analysis. The integration of frequency analysis and thematic categorisation may facilitate a more comprehensive understanding of the linguistic cues that signify satisfaction, developmental advancement, or apprehension within the parental feedback corpus.

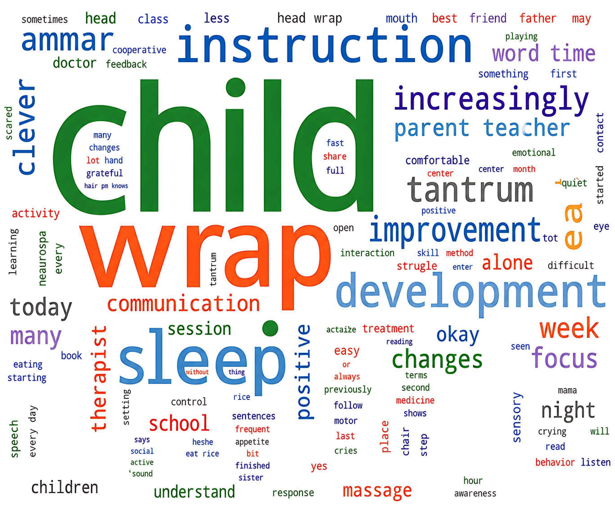

Fig. 5. Word cloud.

D. Topic Modelling Analysis

To discern the underlying thematic structures within these parental testimonies, the LDA was applied to the preprocessed corpus. This unsupervised machine learning methodology facilitated the extraction of prominent word groupings that collectively represented semantically coherent ideas, as expressed by parents. Following a process of iterative optimisation to ensure maximal coherence and interpretability, this model was configured to delineate five distinct topics. The interpretation of each identified topic is subsequently performed based on its most frequently occurring keywords and their contextual associations observed within the dataset, as further detailed in Table 3.

The implementation of the LDA yielded five discernible topics, such as “Progress and Sessions” and “Sleep and Routine,” which encapsulated the principal parental concerns pertaining to therapeutic involvement and everyday routine management.

Table 3. Summary of the LDA topic modelling

Topic	Interpreted Theme	Top Keywords (Selected)
Topic 1	Progress and Sessions	development, session, start, child, change
Topic 2	Behaviour and Transitions	child, eat, change, start, want, although
Topic 3	Sleep and Routine	sleep, night, head, self, wrapping, child
Topic 4	Speech and Emotional Feedback	development, positive, visible, a bit, doctor
Topic 5	School and Play Interaction	teacher, week, school, tantrum, treatment, play

E. Aspect-Based Sentiment Analysis (ABSA)

Leveraging the thematic insights derived from topic modelling, the ABSA was subsequently employed to ascertain the intensity of parental sentiments pertaining to distinct developmental domains. This granular analytical methodology facilitated a more precise assessment of satisfaction levels linked to pivotal behavioural and learning facets manifested among children in post-therapy interventions. The domains identified for analysis encompassed Learning/Academic, Behaviour, Speech/Communication, Interaction/Social, and Sleep. The mean sentiment scores for these domains are delineated in Table 4.

ABSA findings, as outlined in this table, reveal that the domains of Learning/Academic and Behaviour have attained the highest mean sentiment scores, thereby substantiating the practical efficacy of the proposed algorithms in deriving actionable, domain-specific insights from parental testimonials.

Table 4. Aspect-based sentiment analysis

Aspect	Mentions	Average Sentiment	Interpretation
Learning/Academic	11	1.82	Fully positive feedback
Behaviour	25	1.68	Strongly positive
Speech/Communication	21	1.67	Positive improvements
Interaction/Social	30	1.63	Moderately positive
Sleep	17	1.53	Slightly positive

F. *Sentiment Classification Performance*

Subsequent to the descriptive and aspect-based analyses, a supervised machine learning model was constructed for the classification of parental accounts into distinct sentiment categories. To ensure both methodological robustness and interpretability, a pre-established binary classification framework for differentiating between positive and non-positive sentiments was employed. This strategic choice was intended to accentuate the clear divergence between expressions of satisfaction and concern within parental feedback, while also mitigating the intrinsic class imbalance present in the dataset.

The predictive capabilities of this model are delineated in Table 5, which presents the classification report for the testing dataset. The classifier attained an overall accuracy of 0.83, signifying its capacity to correctly predict sentiment polarity for 83% of previously unobserved testimonies. Specifically, the positive class demonstrated particularly strong performance, achieving precision of 0.83, recall of 1.00, and F1-score of 0.91. These results affirmed the efficacy of this model in identifying prevalent positive sentiment patterns, which predominated the dataset and chiefly embodied parental satisfaction with therapeutic achievements.

Table 5. Binary classification report

Sentiment Class	Precision	Recall	F1-score	Support
Non-positive	0.00	0.00	0.00	4.00
Positive	0.83	1.00	0.91	20.00
Accuracy	0.83	0.83	0.83	0.83
Macro average	0.42	0.50	0.45	24.00
Weighted average	0.69	0.83	0.76	24.00

Conversely, the non-positive class exhibited attenuated performance, with registered precision, recall, and F1-score values of 0.00. This limitation could have arisen from pronounced class imbalance, wherein the paucity of neutral and negative instances constrained the capacity of the model to acquire distinctive patterns for non-positive sentiment classes. Consequently, although the classifier exhibited robust performance in recognising prevalent satisfaction indicators, it would chiefly be suited to detecting dominant positive sentiment patterns rather than operating as a comprehensive sentiment analyser.

The confusion matrix further illustrates the classification performance distribution, as presented in Fig. 6. Specifically, all 96 positive instances were accurately classified, while the 22 non-positive instances were erroneously categorised as positive. This outcome suggested that even though the classifier demonstrated considerable efficacy in identifying parental satisfaction, it concurrently exhibited a propensity to favour the dominant class, which is a common observation in sentiment datasets characterised by a significant polarity imbalance. Despite this limitation, the performance of this model aligned with the intrinsic properties of the dataset, given that most parental feedback conveyed positive experiences and negligible expressions of dissatisfaction.

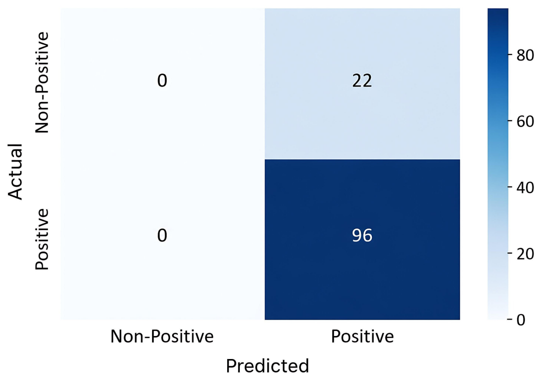

Fig. 6. Confusion matrix.

The stability and consistency of this model have been further corroborated using the cross-validation technique conducted across various folds. Detailed results are presented in Table 6. Notably, this model has consistently demonstrated robust predictive performance for the positive sentiment category, achieving an average precision of 0.81, recall of 1.00, and F1-score of 0.90. This outcome affirmed the strong generalisation capabilities of the classifier across diverse data subsets, thereby underscoring its reliability in discerning prevalent positive sentiment characteristics. While the non-positive class continued to exhibit diminished recall, primarily attributable to its constrained representation within the dataset, the aggregate performance of this model has nonetheless evinced considerable discriminative capacity for predominant sentiment orientations.

Table 6. Cross-validated performance

Class	Precision	Recall	F1-Score	Support
Non-Positive	0	0	0	22
Positive	0.81	1.00	0.90	96

The observed synergy of high accuracy, robust recall, and consistent cross-validation performance have collectively positioned the developed sentiment classifier as an effective automated mechanism for evaluating parental feedback. This, in turn, established its potential as a reliable analytical instrument for large-scale monitoring of satisfaction trends within the therapeutic context.

V. Discussion

The findings of this study may offer considerable insights into how parental feedback, as processed through opinion mining, could inform data-driven educational and therapeutic decision-making for children with autism. The prevalence of positive opinions within parental testimonials may indicate widespread satisfaction with the interventions provided by the studied therapy centre. These opinions may suggest that structured and consistent approaches could be associated with meaningful developmental outcomes. These observations appeared to align with prior research that highlighted the importance of early intervention and sustained parental engagement in enhancing communication, behavioural regulation, and learning readiness among children with autism [36–38]. Moreover, the successful deployment of advanced machine learning models, such as the distilled zero-shot student model, with 84.21% accuracy for emotion detection, as well as the BERT and ChatGPT models demonstrating robust sentiment classification, may indicate the potential of AI-driven tools in processing complex textual data for obtaining actionable insights [10, 39, 40].

The frequent occurrence of positive descriptors, such as "improving," "focused," and "happy" may further suggest an optimistic outlook that could reflect perceived progress and emotional relief among parents. This observation appeared to align with findings from previous studies that have reported high F1-scores (e.g., 0.88–0.91) in sentiment classification for positive reviews, thereby supporting the reliability of such models in discerning positive feedback [40, 41]. However, challenges remain in robustly classifying nuanced or less frequent sentiments, particularly in distinguishing between different negative emotional states, which may require more sophisticated models capable of learning distinctive features from sparse data [39].

While this study may provide valuable insights, it was limited by its relatively small dataset that consisted of 118 parental testimonials sourced from a single therapy centre. This constrained scope may limit the generalisability of the findings to diverse institutional settings, service models, and populations. Therefore, these results should be regarded as exploratory and context-specific rather than broadly representative.

The observed distribution of sentiments may likewise be influenced by institutional contexts, cultural norms, and platform-specific affordances. Notably, cultural inclinations towards politeness and gratitude may contribute to more positively-framed feedback. Moreover, platform characteristics could be associated with variations in sentiment expression, for example, Google Reviews typically elicit public-oriented evaluations, whereas Telegram feedback channels often promote more community-focused and supportive discourses. These contextual elements may partly explain the identified sentiment patterns.

Key parameters, including the number of LDA topics ($k = 5$) and TF-IDF thresholds (max_df = 0.95, min_df = 2), were determined through iterative experimentation informed by previous literature to optimise the balance between topic coherence and interpretability. Preliminary testing with alternative topic numbers suggested either overly fragmented themes or excessively generalised topic structures, thereby impairing semantic clarity.

In addition, a binary sentiment classification framework, which aggregated neutral and negative sentiments into a non-positive category was employed to address class imbalance and bolster model stability. Although this framework diminished sentiment granularity, it may preserve the essential distinction between satisfaction and dissatisfaction, which aligned with the evaluative objectives of this study and may enable the interpretation of predominant parental sentiment patterns.

Topic modelling may provide a deeper understanding by revealing the multidimensional nature of parental feedback, encompassing themes related to academic advancement, emotional stability, social interaction, and routine management. The emergence of topics like "Speech and Emotional Feedback" and "School and Play Interaction" may suggest that parents evaluate their child's progress not solely through clinical milestones but also via observable behaviours in their daily contexts, thereby indicating a positive generalisation of therapeutic gains beyond clinical environments. These insights may be useful for tailoring interventions, as they highlight the need to address the diverse aspects of a child's development, including cognitive, social, and linguistic abilities [33–35]. This observation appeared to be consistent with inclusive education frameworks that advocate for interventions extending beyond therapy sessions [10]. The integration of AI applications may further support this holistic approach by targeting specific psycholinguistic developmental areas [42].

The ABSA analysis may offer a more granular perspective on satisfaction levels across various developmental domains. The most robust positive opinions were observed in the Learning/Academic, Behaviour, and Speech/Communication aspects, which may suggest the effectiveness of therapy practices in addressing core developmental needs. These findings may support the significance of structured, goal-oriented therapy [43–46]. Conversely, the comparatively lower opinions in Interaction/Social and Sleep may indicate persistent challenges in areas requiring environmental adaptation and sensory regulation. This pattern appeared to be consistent with the findings of previous research [31, 32]. Future research could focus on targeted interventions to address these areas and enhance overall well-being [14].

From a methodological standpoint, the sentiment classification model has demonstrated relatively strong accuracy and recall for positive opinions, suggesting that machine learning techniques could be effective in capturing emotional patterns in qualitative parental feedback. The predominance of positive opinions may reflect the underlying data distribution, suggesting that model predictions may align with observed data polarity. These results appeared to be consistent with similar studies [39, 40, 47]. However, accurately classifying less represented sentiment categories remains a methodological challenge due to class imbalance. This issue may lead models to prioritise majority classes, resulting in strong performance for prevalent sentiments but limited precision for minority ones.

The identification of positive parental opinions may have practical implications. Such insights could be used to facilitate targeted enhancements in therapeutic interventions by identifying effective strategies and areas for improvement. Furthermore, understanding ambiguous or conflicting opinions may be important for addressing parental concerns and improving satisfaction. These insights may support clinicians and educators in refining intervention strategies and decision-making processes. By embedding such analyses within feedback systems, therapy centres may foster evidence-based evaluation processes.

Moreover, integrating these insights into educational frameworks and professional training programmes may enhance the development of therapists and intervention specialists [48, 49]. Training initiatives could focus on reinforcing effective practices, while non-positive feedback may guide curriculum refinement. This integration may promote a data-informed approach to professional development. Such continuous feedback loops may be valuable for supporting adaptive, inclusive, and learner-centred interventions.

VI. CONCLUSION

This investigation has critically demonstrated the transformative potential of opinion mining and sentiment analysis as robust methodologies for extracting crucial, data-driven insights from parental feedback regarding autism interventions by therapy centres. By systematically applying topic modelling, ABSA, and supervised sentiment classification, this study has meticulously unveiled dominant emotional patterns and key developmental themes embedded within 118 parental testimonies. A compelling finding was that over 80% of parents expressed positive opinions, which unequivocally indicated a high degree of satisfaction with the therapeutic outcomes, particularly those concerning improvements in critical developmental domains, such as learning progression, behavioural regulation, and speech development. However, the prevalence of positive feedback warrants cautious interpretation, owing to the susceptibility of online testimonial platforms to self-selection bias, whereby satisfied users are often disproportionately inclined to submit reviews. Consequently, elevated positivity may not necessarily reflect comprehensive intervention effectiveness but may partially arise from participation bias inherent in voluntary review systems.

The outcomes of topic modelling further underscored pivotal thematic areas, such as progress monitoring, emotional expression, social engagement, and daily routines that reflected the multifaceted nature of the therapeutic impact of interventions, as perceived by parents. Concurrently, ABSA furnished granular evidence that parental satisfaction was the highest with academic and behavioural advancements, while domains like sleep and social interaction continued to warrant augmented attention. The machine learning classification model, demonstrating high accuracy and recall, corroborated the robustness of computational approaches for evaluating qualitative data based on sentiments.

The principal contribution of this study resides in its illustration of the systematic conversion of parental feedback into quantitative metrics that could facilitate data-informed decision-making in educational and therapeutic domains. By elucidating predominant themes and sentiment profiles, the proposed framework could afford practical utility to therapists, educators, and policymakers pursuing evidence-based programme enhancements.

Collectively, these results corroborated the notion that integrating data-driven sentiment analytics into evaluation frameworks for therapy centres could augment evidence-based decision-making processes and reinforce feedback mechanisms among parents, therapists, and educators. This methodological approach could significantly contribute to the broader objective of data-informed education, wherein experiential insights from stakeholders are transmuted into actionable intelligence for programme refinement.

Nevertheless, this study was constrained by several limitations, including its reliance on a small, single-centre dataset and class imbalance across sentiment categories, which may compromise generalisability and model performance. These limitations emphasised that the findings should be interpreted as exploratory and context-bound, reflecting a single-centre dataset, and therefore require cautious interpretation.

Prospective research endeavours should extend this conceptual framework by incorporating a more expansive and heterogeneous dataset spanning multiple therapy centres to facilitate cross-contextual comparisons of parental perceptions. Furthermore, the deployment of advanced hybrid models, which integrate linguistic and behavioural data, could enhance predictive accuracy and interpretability. Longitudinal sentiment tracking also has the potential to unveil temporal shifts in parental attitudes, thus offering invaluable indicators of therapeutic consistency and long-term developmental trajectories. Future research could also employ resampling techniques like the SMOTE, evaluate alternative classifiers, and adopt supplementary metrics, including balanced accuracy or the Matthews Correlation Coefficient to enhance the robustness of the developed model. Furthermore, embedding the proposed opinion mining framework within educational technology systems (e.g., dashboards or decision-support tools) could empower practitioners and administrators to track parental feedback trends and facilitate data-informed intervention planning.

Future research could mitigate the identified limitations by augmenting the dataset across multiple therapy centres, implementing longitudinal sentiment monitoring, and exploring hybrid models that fuse textual sentiment analysis with behavioural and clinical metrics. Subsequent studies could advance this line of inquiry by investigating deep learning and transformer-based architectures, such as the BERT or hybrid deep sentiment classifiers to better discern contextual subtleties and intricate linguistic structures. Broadening the dataset to incorporate larger, more diverse samples would further enable the rigorous evaluation of these advanced models in authentic, large-scale settings.

In summation, this study reasserts the intrinsic value of opinion mining in bridging qualitative parental feedback with quantitative educational analytics. The incorporation of AI-driven sentiment analysis has not only furnished an efficacious evaluation mechanism but also delineated a strategic pathway towards more responsive, inclusive, and data-informed practices in autism intervention.

ETHICAL CONSIDERATION

All data utilised in this study have been sourced from publicly accessible platforms and anonymised prior to analysis. No personally identifiable information was collected or disclosed. As the research constituted secondary analysis of public data without direct interaction with human subjects, formal ethical approval was not required under institutional guidelines. Nonetheless, the authors acknowledge the sensitive nature of parental testimonials regarding children with ASD and have taken precautions to minimise potential risks associated with misrepresentation or stigmatisation.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

M.W. led the development of this study, including conceptualisation, methodology, data analysis, and manuscript preparation. I.S.C.I. and S.R. contributed to data processing, model development, and validation. N.M.Z. and N.A.M.R. assisted with literature review, statistical analyses, and interpretation of findings. N.A.H. and N.F.M.T. provided editorial support, documentation, and proofreading. All authors have reviewed and approved the final manuscript.

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