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RESEARCH ARTICLE

Global Perspectives on Laptop Features: A Sentiment Analysis of User Preferences in Developed and Developing Countries

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ABSTRACT This study examines laptop user sentiments across developed and developing countries using aspect-based sentiment analysis (ABSA) on social media data. Employing a mixed-methods approach, the research combines large-scale sentiment analysis of 1,467,535 tweets with expert insights gathered through a Delphi panel of ten industry professionals. The study analyzes user opinions on 16 key laptop features, revealing distinct preferences and pain points between users in developed and developing nations. Findings show that consumers in developing countries express higher overall satisfaction, while those in developed countries demonstrate more critical views, particularly regarding performance-related features. Universal concerns include battery life and cooling efficiency. The research identifies key priorities for each market: high performance and advanced features for developed countries, and affordability, durability, and reliability for developing nations. Based on these insights, the study proposes tailored strategies for laptop manufacturers, including differentiated product lines, universal charging solutions, and market-specific innovations in cooling systems and warranties. The methodology incorporates data preprocessing, ABSA implementation using the PyABSA framework, and a three-phase Delphi process for expert analysis. This comprehensive analysis provides valuable guidance for product development and marketing strategies in the global laptop industry, emphasizing the importance of market-specific approaches to enhance user satisfaction and maintain competitiveness. The study also acknowledges limitations and suggests directions for future research, including multi-source data analysis and longitudinal studies.

INDEX TERMS Notebook computers, consumer behavior, customer preferences, social media analytics, laptop industry.

I. INTRODUCTION

The global electronics industry is undergoing a transformative period, with laptops and notebooks emerging as critical tools that shape modern work, education, and lifestyle patterns across diverse global demographics [1], [2], [3]. This transformation is particularly significant due to an unprecedented convergence of three key developments: the evolution of laptops from optional devices to essential productivity tools, the emergence of social media as a rich source of consumer insights, and the increasingly distinct needs of developed versus developing markets. As digital technologies become more deeply embedded in daily life, laptops have transcended their traditional role as computing devices to become fundamental enablers of global connectivity, remote work, distance learning, and digital innovation [2], [4], [5], [6].

This evolution in laptop usage coincides with a revolutionary change in how consumers share their experiences and preferences. The exponential growth of social media platforms has created an unprecedented ecosystem of real-time, unfiltered consumer feedback about technology products [7], [8], [9].

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This massive volume of user-generated content presents a unique opportunity to understand consumer behavior at a scale and depth previously impossible with traditional market research methods [3], [10]. By applying advanced sentiment analysis techniques to this rich data source, researchers and manufacturers can now uncover subtle patterns and preferences that were previously invisible, leading to more informed product development decisions [11], [12], [13].

However, the laptop market is not homogeneous, and consumer needs and expectations can vary significantly across different user segments [14], [15]. One key differentiating factor is whether consumers reside in developed or developing countries [16], [17]. The profound economic, infrastructural, and cultural distinctions between these contexts fundamentally shape how users interact with and evaluate laptop products [18], [19]. For instance, while users in developed countries might prioritize advanced performance features and seamless ecosystem integration, those in developing nations often focus on durability, reliability, and long-term value. Understanding these nuanced differences is vital for manufacturers seeking to optimize their product offerings, yet current research lacks a comprehensive framework for analyzing and addressing these distinct market needs.

This study makes several significant contributions to both academic literature and industry practice. First, it introduces an innovative methodological framework that combines large-scale aspect-based sentiment analysis of social media data with expert validation through a structured Delphi method. This hybrid approach transcends the limitations of purely quantitative or qualitative methods, providing a more comprehensive and reliable understanding of consumer preferences across different economic contexts.

Second, this research significantly extends the current understanding of technology adoption patterns by developing a systematic comparison of user sentiments between developed and developing nations. While previous studies have examined laptop features or user preferences in isolation, our work is the first to provide an empirically grounded analysis of how economic, infrastructural, and cultural factors influence consumer expectations and satisfaction across markets. This contribution is particularly valuable given the increasing importance of emerging markets in the global technology sector.

Third, this study advances the field of sentiment analysis by applying sophisticated aspect-based techniques to a complex, multi-feature product category. The research demonstrates how advanced natural language processing methods can be effectively combined with domain expertise to generate actionable insights, establishing a methodological template for future studies in consumer electronics and related fields.

Fourth, the research bridges the crucial gap between data-driven analysis and practical implementation by developing specific, market-tailored recommendations for manufacturers. By identifying distinct preference patterns and pain points across different economic contexts, this study provides manufacturers with concrete guidance for product development, feature prioritization, and marketing strategies.

To systematically address these contributions, this research examines the following key questions:

1. How do user sentiments toward specific laptop features differ between developed and developing countries, and what underlying factors drive these differences? This question explores the nuanced relationships between economic context and consumer expectations.
2. What are the critical pain points and satisfaction drivers for laptop users across different economic contexts, and how do these influence product requirements? This investigation reveals how varying infrastructure, usage patterns, and economic conditions shape user needs.
3. How can manufacturers effectively adapt their product development and marketing strategies to address the distinct needs of users in developed versus developing markets? This question bridges theoretical insights with practical applications.

These questions are particularly relevant given the increasing globalization of the laptop market and the growing importance of emerging economies. The findings from this research not only contribute to academic understanding but also provide manufacturers with evidence-based guidance for market-specific product optimization.

The remainder of this article is structured as follows: Chapter 2 provides a review of relevant literature. Chapter 3 outlines the research methodology employed. Chapter 4 presents a detailed analysis of the study's findings. Chapter 5 discusses the results in relation to the research questions and explores potential managerial implications. Finally, Chapter 6 offers a summary and conclusion of the research.

II. LITERATURE REVIEW

Sentiment analysis is a computational method used to identify and categorize opinions in text, particularly in terms of polarity (positive, negative, or neutral). Its applications span diverse industries, from marketing to politics, and have expanded significantly with the growth of social media platforms. Traditional techniques, such as lexicon-based approaches, have evolved into machine learning and deep learning models that handle the complexity of unstructured data on platforms like Twitter, Facebook, and Instagram [20], [21]. Social media offers an unprecedented volume of user-generated content, making sentiment analysis invaluable for deriving insights from consumer behavior [22]. Analyzing this data provides a clear understanding of public opinion and is applied in numerous fields, including marketing, healthcare, and customer service [23].

A. SENTIMENT ANALYSIS MODELS, TECHNIQUES, AND ASPECT-BASED SENTIMENT ANALYSIS (ABSA)

Sentiment analysis (SA) has advanced significantly over the past two decades, evolving from traditional lexicon-based

TABLE 1. Overview of sentiment analysis models and techniques for ABSA in previous studies.

Title	Year	Models Used	Key Findings
Enhancing deep learning sentiment analysis with ensemble techniques in social applications	2017	Ensemble techniques (CNN, traditional surface classifiers)	Introduced ensemble models combining deep learning and traditional classifiers, improving sentiment classification performance.
Deep learning for sentiment analysis: A survey	2018	Deep Learning (CNN, RNN), Sentiment Analysis	Surveyed deep learning approaches in sentiment analysis, highlighting their effectiveness in sentiment classification.
Deep Learning-Based Frameworks for Aspect-Based Sentiment Analysis	2020	Deep Learning (CNN, RNN), ABSA	Deep learning provides state-of-the-art performance for ABSA, without the need for intensive feature engineering.
SEML: A Semi-Supervised Multi-Task Learning Framework for Aspect-Based Sentiment Analysis	2020	Bi-LSTM, Semi-supervised Learning, Multi-task Learning	Proposed a multi-task learning framework for ABSA with high accuracy using semi-supervised techniques.
Deep Learning Techniques for Aspect-Based Sentiment Analysis	2022	Deep Learning, ABSA, CNN, LSTM	Review of deep learning techniques for ABSA with a focus on their accuracy and granularity.
Pelican Optimization Algorithm with Deep Learning for Aspect-based Sentiment Analysis on Asian Low Resource Languages	2023	BERT, Attention-based Bi-LSTM, Pelican Optimization Algorithm	Developed a novel optimization algorithm with deep learning, significantly improving ABSA for low-resource languages.
Leveraging Deep Learning Models for Automated Aspect-based Based Sentiment Analysis and Classification	2023	CNN, Bi-LSTM, Hopfield Network	Deep learning models (CNN and Bi-LSTM) performed better than traditional methods for aspect-based sentiment analysis.
Aspect-based sentiment analysis using smart government review data	2024	Deep Learning, ABSA, CNN, LSTM	Lexicon and rule-based approach improves aspect extraction accuracy for government app reviews, outperforming SVM by 5%

methods to sophisticated machine learning (ML) and deep learning (DL) approaches. This progression has enhanced both the accuracy and granularity of sentiment classification, especially for Aspect-Based Sentiment Analysis (ABSA), which provides a fine-grained view of sentiments tied to specific product aspects.

In its early stages, sentiment analysis predominantly relied on lexicon-based approaches, using resources such as SentiWordNet [24], [25] to classify words into predefined sentiment categories (positive, negative, neutral). Although effective for basic sentiment detection, these methods struggled with nuanced language, such as sarcasm and mixed sentiments within a single sentence [26]. With the introduction of machine learning, models like Support Vector Machines (SVM) and Naive Bayes (NB) improved sentiment classification by learning from labeled data, though they required extensive feature engineering, which limited flexibility and scalability [27], [28].

Machine learning techniques, including Random Forests and Logistic Regression, enhanced sentiment analysis by leveraging statistical learning. These models identified patterns based on word frequencies and text relationships but faced challenges in capturing the complexity of human language [29]. The shift to deep learning marked a significant advancement. Deep learning models, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) such as Long Short-Term Memory (LSTM), enabled automatic feature extraction and a deeper understanding of textual data by capturing both syntactic and semantic features without extensive feature engineering [30], [31]. CNNs became widely adopted for sentiment analysis due to their ability to identify local patterns, while LSTMs excelled in understanding sequential dependencies. More recently, transformer-based models like BERT (Bidirectional Encoder Representations from Transformers) have set a new standard in sentiment analysis and natural language processing (NLP) tasks. BERT's bidirectional nature allows it to capture contextual relationships effectively, significantly improving sentiment classification accuracy [32].

Aspect-Based Sentiment Analysis (ABSA) extends traditional sentiment analysis by focusing on specific components or "aspects" of a product, rather than general sentiment. ABSA performs two essential tasks: aspect extraction, identifying specific elements of a product mentioned in text (e.g., CPU, RAM, battery in laptops), and sentiment classification, determining the polarity (positive, negative) of the sentiment associated with each aspect [33], [34]. This level of detail makes ABSA highly valuable in domains like electronics, retail, and hospitality, where customer feedback often targets specific product features [35], [36], [37], [38]. ABSA initially used traditional machine learning techniques like SVM and NB, which required manual feature engineering. However, deep learning models such as LSTMs and CNNs have enabled automatic aspect extraction and sentiment classification, improving both accuracy and scalability [39], [40], [41]. Advanced models integrating transformers, such as BERT with attention mechanisms, have further enhanced ABSA's effectiveness, achieving high accuracy in aspect extraction and sentiment classification across diverse applications [42], [43], [44].

By isolating aspect-specific sentiments, ABSA provides actionable insights for industries reliant on customer feedback. In the laptop industry, for instance, ABSA can reveal user opinions on distinct features such as battery life or

TABLE 2. Summary of ABSA applications in previous studies.

Domain	Year	Application	Methodology	Key Findings
Restaurants, Laptops	2014	SemEval-2014 ABSA for restaurant and laptop reviews	ABSA	Demonstrated the effectiveness of ABSA for aspect extraction and sentiment classification
Restaurant Reviews	2017	ABSA for Indonesian restaurant reviews	SVM, Lexicon Approach	High F1 scores in aspect categorization and sentiment classification for restaurant reviews
Hotel Reviews	2017	ABSA for hotel reviews	Neural Network	Achieved superior performance in aspect extraction and rating prediction using neural networks
Online Retail	2018	Sentilyzer for Amazon product reviews	ABSA, Sentiment Lexicon	Aspect-oriented sentiment analysis from reviews improved purchasing decisions and product improvement
Electronics Devices	2019	Aspect extraction for electronic devices	Maximum Entropy Model	Extracted multi-grained aspects from reviews with high accuracy in electronics product reviews
Government Reviews	2020	ABSA for government smart applications	Lexicon-based Approach	Improved accuracy in extracting aspects of customer reviews for government services
Mobile Phones	2021	ABSA for iPhone reviews	Machine Learning, SVM	Identified critical aspects like camera and performance through ABSA, improving product reviews accuracy
Product Reviews	2021	ABSA for product reviews in 5G networks	Ensemble Learning	Improved predictive accuracy using a multi-aspect model in 5G network applications
Laptops	2022	ABSA for laptop feature analysis	ABSA, Random Forest	Identified key product aspects through ABSA, leading to improved product recommendations
Movie Reviews	2023	ABSA for movie reviews	Logistic Regression	Achieved high accuracy in aspect and sentiment prediction for movie reviews
Cellphones & Apps	2024	ABSA for cellphone and app reviews	Word embedding and RO-EASGB hybrid model	The hybrid model, utilizing CNABE for embedding and RO-EASGB for classification, achieved superior accuracy and efficiency over baseline models in aspect-based sentiment analysis

display quality. This fine-grained understanding allows manufacturers to prioritize product improvements and better align with consumer needs. ABSA is particularly effective when combined with real-time applications like social media monitoring and customer feedback analysis, where the depth of insights into individual product aspects can inform targeted product development and marketing strategies [45], [46].

As demonstrated in Table 1, several studies have explored various sentiment analysis models and techniques, including the evolution from traditional machine learning approaches to more advanced deep learning models such as CNNs, LSTMs, and hybrid methods, all contributing to the ongoing development of Aspect-Based Sentiment Analysis (ABSA).

B. APPLICATIONS OF SENTIMENT ANALYSIS AND ABSA

1) GENERAL APPLICATIONS OF SENTIMENT ANALYSIS

Sentiment analysis is applied in a variety of domains, including healthcare, politics, finance, and customer reviews [47], [48], [49], [50], [51]. It plays a key role in understanding public opinion during significant events or assessing customer satisfaction with products [52], [53], [54]. The use of sentiment analysis in social media platforms provides industries with valuable insights into customer preferences, facilitating the development of targeted marketing strategies [6].

2) APPLICATIONS OF ABSA IN SOCIAL MEDIA ANALYSIS

ABSA has been widely applied in social media to extract detailed insights from consumer reviews [26], [55], [56], [57]. Its ability to classify sentiments based on specific product aspects provides valuable feedback for product development. For instance, ABSA has been used to analyze user-generated reviews for mobile phones and laptops, offering companies insights into which features are most valued by customers [58], [59]. In social media marketing, ABSA has proven effective in identifying trends and consumer preferences, which is essential for crafting targeted marketing campaigns [60], [61]. In the notebook and laptop industry, ABSA has proven to be an effective tool for extracting valuable insights from user reviews. By focusing on specific aspects such as processing power, display quality, and battery life, ABSA provides manufacturers with a clearer understanding of customer preferences [62], [63]. The application of ABSA in this domain allows companies to prioritize product features that matter most to consumers, leading to better product designs and higher customer satisfaction [64]. Table 2 provides a summary of the applications of ABSA and sentiment analysis in various domains as explored in previous studies.

This research advances both methodological rigor and practical applicability through several significant innovations in the application of Aspect-Based Sentiment Analysis

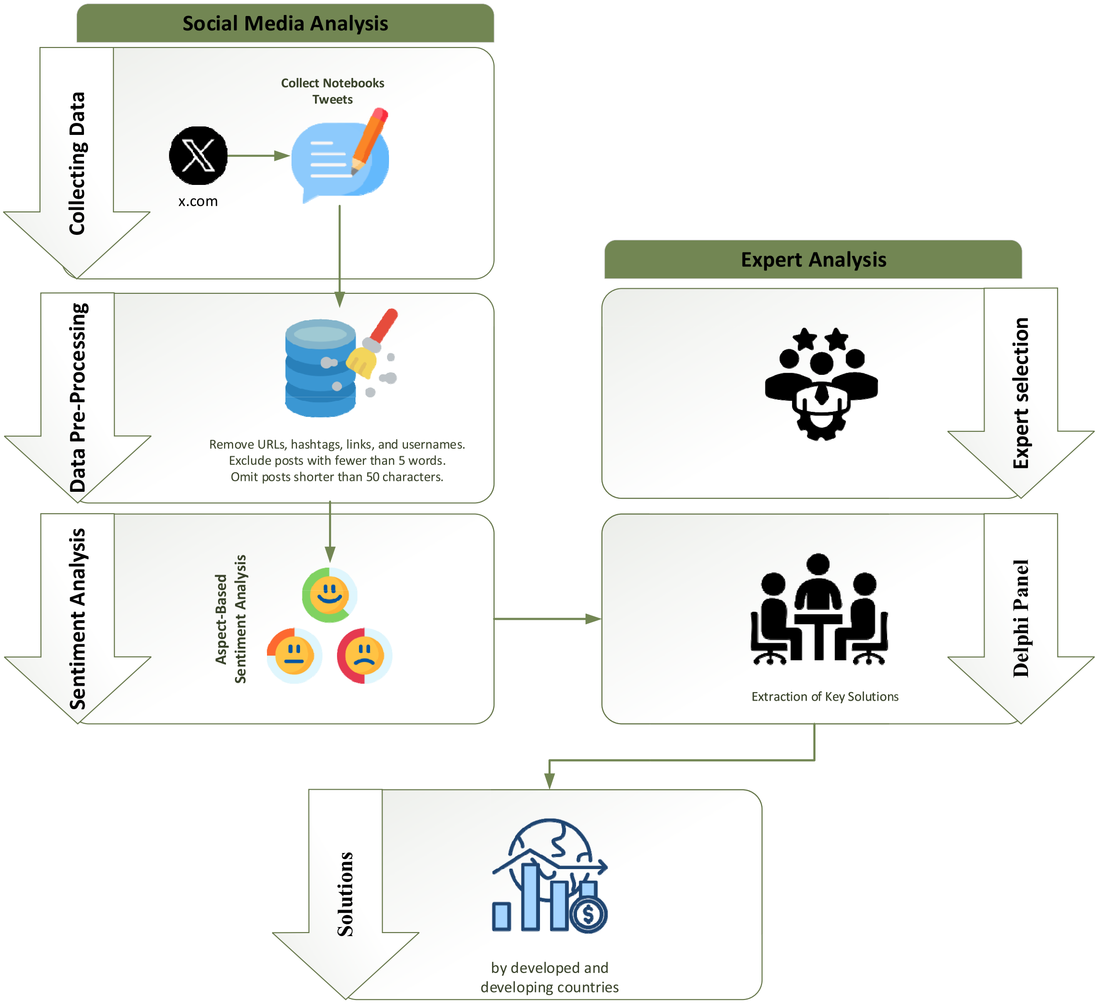

FIGURE 1. **Research methodology.**

(ABSA) to the notebook industry context. Our approach represents a substantial technical advancement over previous studies through its comprehensive integration of multiple analytical layers and sophisticated processing techniques.

The technical innovation of our work is manifested in the development of a robust three-layer validation framework that uniquely combines machine learning, expert verification, and cross-cultural analysis. We have developed a sophisticated data preprocessing pipeline capable of handling multiple languages and regional variations, while implementing advanced ABSA techniques to process an unprecedented volume of over 1.4 million tweets. This scale significantly exceeds previous studies in the field. Our framework further incorporates geolocation-based market segmentation with sentiment analysis, enabling precise regional comparisons through custom modifications to the PyABSA framework for multi-language processing.

From a methodological perspective, our research introduces several notable contributions to the field. We have pioneered the combination of large-scale sentiment analysis with structured expert validation through the Delphi method, while developing a comprehensive feature categorization system specifically tailored to laptop components. This approach enables systematic comparison of consumer sentiments across economic contexts, supported by rigorous data cleaning protocols that ensure high-quality input for sentiment analysis.

While previous studies have applied ABSA across various domains such as mobile phones, restaurants, and general product reviews, our research distinguishes itself through its innovative technical framework. This framework processes and analyzes user-generated content across multiple languages, employing advanced translation algorithms and region-specific sentiment dictionaries. Furthermore, our methodology incorporates sophisticated geo-tagging and economic classification systems, enabling precise segmentation of user feedback between developed and developing markets.

The technical robustness of our approach is enhanced through several key elements. We implement systematic validation of sentiment classifications through expert panel review, alongside advanced noise reduction techniques specifically designed for social media data. Our custom preprocessing algorithms handle regional language variations with high precision, while statistical validation methods ensure result reliability. The integration of temporal analysis accounts for evolving consumer preferences, providing a dynamic view of market trends.

Our research extends beyond traditional single-market or feature-specific analyses by implementing a comprehensive analytical framework that addresses multiple dimensions of consumer sentiment. This framework processes multi-language content while maintaining semantic integrity, accounts for regional variations in expression and sentiment, and incorporates economic and infrastructural contexts into the analysis. The validation of findings occurs through both quantitative metrics and expert assessment, ensuring robust and reliable results.

The integration of expert input through the Delphi method adds another layer of technical validation, distinguishing this study from purely data-driven approaches. Our panel of ten industry experts, selected through rigorous criteria, provides crucial validation of the sentiment analysis results and helps ensure the practical relevance of our findings. This comprehensive technical framework enables us to deliver insights that are both methodologically sound and practically applicable, addressing a critical gap in existing research by providing manufacturers and marketers with reliable, actionable data for understanding and addressing the diverse needs of consumers across different economic contexts.

III. METHODOLOGY

This research adopts a robust methodology to analyze user sentiments regarding laptop features in developed and developing countries. It leverages social media data and expert insights through a structured process, involving data collection, preprocessing, sentiment analysis, and expert validation. The process flow is outlined in Figure 1.

A. DATA COLLECTION

The data collection methodology employed the X API with a systematic query-based approach. A predefined set of feature-specific keywords was used to extract relevant tweets, with each tweet processed to capture both content and metadata including geolocation information for economic context classification. Additionally, the geolocation metadata of each tweet is used to categorize users into developed or developing countries.

The data collection framework incorporated automated tagging mechanisms to classify tweets based on feature relevance and geographical context, enabling systematic categorization of user feedback across economic regions.

Let D represent the set of collected tweets, with $D = \{d_1, d_2, \ldots, d_n\}$, where each d_i contains feature keywords, location tags, and timestamp information. This dataset serves as the foundation for subsequent steps in the analysis.

B. DATA PRE-PROCESSING

To ensure data quality, the tweets undergo a rigorous preprocessing pipeline, preparing them for sentiment analysis [65], [66]. Preprocessing is essential for removing noise, standardizing data, and enhancing feature extraction. The steps are as follows:

- Removal of URLs, Hashtags, Links, and Usernames: Non-text elements are removed to reduce noise [67].
- Exclusion of Posts: Posts with fewer than five words or fewer than 50 characters are omitted, focusing on meaningful content.
- Text Normalization: Text is converted to lowercase, and punctuation is removed.
- Tokenization and Lemmatization: Each tweet d_i is split into tokens $T = \{t_1, t_2, \ldots, t_m\}$, and each token is lemmatized to standardize word forms.
- Stop Word Removal: Common words (stop words) are filtered out, improving focus on sentiment-bearing terms.

Each tweet d_i can be represented as a token sequence $T = \{t_1, t_2, \ldots, t_m\}$, where t_i denotes tokens relevant to the sentiment analysis. These tokens undergo a feature extraction process, generating a feature vector F_i for each tweet. The preprocessed dataset, $D' = \{d'_1, d'_2, \ldots, d'_n\}$, forms the input for the sentiment analysis phase.

C. SENTIMENT ANALYSIS

The sentiment analysis phase employs the PyABSA (Python Aspect-Based Sentiment Analysis) framework, which provides pre-trained models specifically optimized for aspect-based sentiment analysis tasks. PyABSA leverages transformer-based architectures, like BERT, to extract both aspect terms and associated sentiments from text data, achieving high granularity in sentiment classification. [68], [69].

Using PyABSA, we implement a two-step process:

Aspect Extraction: For each tweet $d'_i \in D'$, PyABSA identifies aspect terms $A_i = \{a_{i1}, a_{i2}, \ldots, a_{ik}\}$ related to laptop features. An aspect term extraction model, based on BERT's attention mechanism, isolates these terms with high accuracy.

Sentiment Classification: Each aspect a_{ij} is assigned a sentiment $s_{ij} \in \{\text{positive, negative}\}$ using PyABSA's classifier.

For each tweet, the model outputs a set of aspect-sentiment pairs:

$$S\left(d'_i\right) = \{(a_{i1}, s_{i1}), (a_{i2}, s_{i2}), \ldots, (a_{ik}, s_{ik})\}$$

The sentiment analysis is conducted separately for tweets from developed and developing countries, facilitating a comparative analysis. PyABSA's fine-tuned BERT model uses a multi-layer bidirectional approach to capture contextual relationships in text, yielding nuanced sentiment classifications across economic contexts.

D. EXPERT ANALYSIS

The expert analysis phase consists of two crucial steps:

1) EXPERT SELECTION

This stage aims to identify and recruit experts who specialize in the laptop industry from both developed and developing countries. The selection process ensures a balanced representation of expertise across different economic contexts.

2) DELPHI PANEL

Separate Delphi panels are formed for experts from developed and developing countries. In each panel, the five aspects that received the most negative sentiments in their respective economic contexts (developed or developing countries) are selected for further analysis. These aspects are then presented to the expert panels to generate solutions and recommendations [70], [71].

E. SOLUTION EVALUATION AND PRIORITIZATION

The solutions proposed by the expert panels are evaluated and scored. This process identifies the main strategies to address negative sentiments and user concerns for the selected aspects, tailored specifically for developed and developing countries.

F. FINAL ANALYSIS AND RECOMMENDATIONS

The research concludes by synthesizing the insights from the sentiment analysis and expert recommendations. This final step provides a comprehensive set of strategies for laptop manufacturers to improve user satisfaction and address concerns, with specific recommendations for both developed and developing markets.

This methodology enables a nuanced understanding of user sentiments towards laptop features across different economic contexts, while also providing actionable insights for manufacturers to improve their products and marketing strategies in a targeted manner.

Here's the pseudocode summarizing the full implementation of the methodology in Algorithm 1:

Algorithm 1 Aspect-Based Sentiment Analysis With Delphi Panel Validation

Input: Dataset D (tweets with laptop features),
Economic_Categories (developed, developing)
Output: Feature-Specific Sentiments, Expert-Validated Recommendations

```
// Data Collection
Initialize D as collection of tweets from X platform
 for each tweet d_i ∈ D do
    Extract feature keywords
    Classify d_i based on geolocation into developed or developing
 end for

// Data Pre-Processing
for each tweet d_i ∈ D do
    Clean text: remove URLs, hashtags, and usernames
    Standardize: lowercase, remove punctuation
    Tokenize and lemmatize text
    Remove stop words
end for
Store preprocessed data as D′

// Aspect-Based Sentiment Analysis using PyABSA
Initialize PyABSA model with transformer-based architecture
for each tweet d_i' ∈ D' do
    Extract aspects A_i = {a_ij} using aspect extraction model
    Classify sentiment s_ij for each aspect a_ij
    Store aspect-sentiment pairs S(d_i') = {(a_ij, s_ij)}
 end for

// Expert Analysis with Delphi Method
Initialize Expert Panels E_d for developed and E_dev for developing
for each aspect a_ij with high negative sentiment do
    Present feature to experts
    Experts generate solutions R_i = {r_ik}
    Experts rate solutions on Likert scale
end for
Aggregate highest-rated solutions as R*

 return Aspect-Sentiment Pairs S, Expert-Validated Recommendations R*
```

IV. RESULTS

A. DATA COLLECTION

The initial stage of our research involved collecting user opinions on notebook products from the social media platform X (formerly known as Twitter) [72]. This platform has been chosen because of its large user base and the abundance of user-generated content, making it a valuable source for gathering public opinions and sentiments [73]. To ensure a comprehensive and representative dataset, X API has been used, to extract tweets spanning a four-year period, from January 2020 to July 2024 [74].

To compile the dataset, a query-based search methodology was employed. This involved generating a comprehensive list of keywords directly related to various features of laptops. These keywords were selected based on the most important aspects of laptops that consumers typically discuss. The query list included terms such as "RAM," "Display," "Battery," "Design," and many others, covering a broad spectrum of laptop features. Table 3, shows the query for English:

To address the global nature of user reviews, the query list was translated into over 10 different languages, ensuring a broad capture of relevant data. However, the final analysis focused on the top four languages, English, Spanish, Japanese, and Arabic, which accounted for over 80% of the collected tweets. Non-English tweets were automatically

TABLE 3. Query list created for English.

LANGUAGE	QUERY LIST
ENGLISH	"ram, display, keyboard, price, battery, storage, GPU, CPU, charger, warranty, design, webcam, port, size, fan, weight, software, hardware, mouse, security, operating system, SSD, hard disk, LCD, Graphic, HDD, Resolution, Power Adapter, USB, HDMI, screen, processor, windows, performance, touchscreen, memory, monitor, Bluetooth, touchpad, trackpad"

translated into English to maintain consistency in the dataset and to ensure effective sentiment analysis, as the methods used perform more reliably on English text. The translation was carried out using a widely used translation API, which detects the original language and converts the content into English. The distribution of tweets over four languages is shown in Table 4.

TABLE 4. Distribution of tweets by language.

LANGUAGE	NUMBER OF TWEETS
ENGLISH	733767
SPANISH	220130
JAPANESE	146753
ARABIC	73376
OTHER LANGUAGES	293509
TOTAL	**1467535**

The X API's geolocation attributes were instrumental in distinguishing between tweets from developing and developed countries [75]. Using the World Economic Situation and Prospects 2024 report (WESP 2024) published by the United Nations, the tweets were categorized accordingly. Developed countries included nations such as the United States, Canada, the United Kingdom, Germany, Japan, and Australia, as well as several European Union countries like France, Italy, and the Netherlands. On the other hand, developing countries included a broad range of nations, such as India, Brazil, Nigeria, Egypt, and Indonesia. This division allowed us to analyze and compare sentiment trends between these two distinct economic groups, providing insights into regional variations in consumer opinions.

Tweets were gathered during a specific timeframe from January 2020 to July 2024, a period selected to ensure the dataset reflected recent trends and user opinions. Initially, over 1467535 tweets were compiled. To improve the quality and reliability of the dataset, a filtering criterion was implemented, including only tweets that had received at least one 'like'.This strategy helped to eliminate potentially less relevant or less influential reviews.

To illustrate the temporal distribution of the reviews, a time trend chart was created, depicting the frequency of reviews from both developed and developing countries over the specified period. The review count represents the number of tweets captured each day. Figure 2, presents the smoothed frequency of reviews, highlighting significant trends and peaks in user activity. Notably, the number of tweets increased rapidly for both developed and developing countries at certain points, with a particularly sharp rise for developed countries during the last five months (February 2024 to July 2024). Additionally, the overall trend for developing countries shows a consistent increase in tweet volume throughout the entire period.

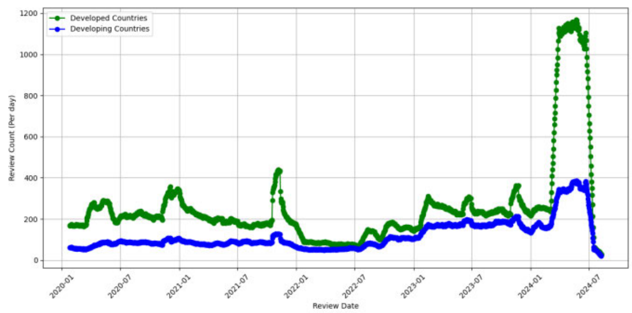

FIGURE 2. Temporal distribution of tweets from developed and developing countries.

B. DATA PRE-PROCESSING

To ensure the quality and consistency of the dataset, a comprehensive data preprocessing pipeline was implemented. This process was essential to prepare the data for subsequent Aspect-Based Sentiment Analysis (ABSA) and to enhance the reliability of the analysis.

1) DATA CLEANING OUTCOMES

The implementation of our preprocessing pipeline resulted in the refinement of the initial 1,467,535 tweets to approximately 800,000 high-quality reviews. This significant reduction reflected the stringent quality criteria applied to ensure data reliability. Duplicate reviews, identified as entries with identical text, were removed to avoid redundancy and over-representation of certain opinions [76]. This initial cleaning reduced the dataset from 1467535 tweets to approximately 800,000 high-quality reviews.

2) TEXT PROCESSING RESULTS

The application of text cleaning protocols resulted in a significantly refined dataset. The filtering process removed approximately 40% of the initial tweets that didn't meet the minimum quality criteria, including posts with insufficient content length or lack of meaningful engagement.

Filtering Short Reviews: To further refine the dataset, reviews with fewer than 5 words or less than 50 characters were excluded. This filtering ensured that only substantial and potentially meaningful reviews were retained for analysis.

Also, further preprocessing including advanced text processing techniques such as stop word removal, tokenization, Part-of-Speech (POS) tagging, and stemming was applied to get high-quality reviews [47], [77].

3) LANGUAGE DISTRIBUTION ANALYSIS

The translation process revealed significant linguistic diversity in the dataset, with content spanning over 10 languages. The final analysis focused on the four predominant languages (English, Spanish, Japanese, and Arabic), which collectively represented over 80% of the total dataset. This step was crucial in ensuring language uniformity, as the sentiment analysis methods were used to perform more effectively on English text, leading to more accurate and meaningful results.

C. ASPECT-BASED SENTIMENT ANALYSIS IMPLEMENTATION

1) DEEP LEARNING AND SENTIMENT ANALYSIS

Deep learning techniques have revolutionized sentiment analysis and social media analysis due to their ability to handle large volumes of unstructured data with high accuracy. These methods enable models to understand complex language patterns and contexts, improving the extraction and classification of sentiments in large datasets. Deep learning models, such as those used in ABSA, are now integral to analyzing social media content, where users frequently discuss multiple aspects of a product in informal language [78].

Sentiment analysis is a branch of natural language processing (NLP) that focuses on identifying and classifying opinions or sentiments expressed in a given text. It is commonly used in applications such as product reviews, social media monitoring, and customer feedback analysis to gauge user opinions. By analyzing sentiments, companies can gain valuable insights into customer satisfaction, market trends, and overall product or service perception. Sentiment analysis is widely adopted due to its ability to convert subjective opinions into structured data, facilitating data-driven decision-making [79].

2) ASPECT-BASED SENTIMENT ANALYSIS (ABSA)

Aspect-based sentiment Analysis (ABSA) is a more granular form of sentiment analysis, where instead of analyzing the overall sentiment of a text, the focus is on specific aspects or features mentioned within it. ABSA allows the extraction of opinions about particular components of a product or service, enabling deeper insights into what users like or dislike. For example, in laptop reviews, users may express varying sentiments about features such as the "battery," "RAM," or "price," and ABSA helps to isolate and analyze these sentiments. This approach is particularly useful in reviews and feedback where multiple aspects are discussed [55], [74].

The PyABSA library, a robust Python-based framework designed specifically for Aspect-Based Sentiment Analysis, was utilized. PyABSA provides access to pre-trained models capable of extracting aspects from reviews and determining the sentiment for each aspect (positive, or negative).

3) FEATURE EXTRACTION

One of the critical tasks in our work was identifying the relevant features to be analyzed. After performing ABSA on the collected reviews, aspects were extracted for each review, and their corresponding sentiments were identified [47], [61]. The extracted aspects were analyzed to determine the most frequently discussed features among the reviews, revealing which aspects users are most concerned about.

The 16 most common aspects in the reviews were identified, forming the basis for further analysis. These aspects included core laptop features such as 'ram,' 'display,' 'battery,' 'price,' and 'keyboard.' Once identified, the ABSA model was used to analyze the sentiment associated with each of these aspects across all reviews. The 16 target aspects identified were: [RAM, display, keyboard, price, battery, storage, GPU, CPU, charger, warranty, design, webcam, port, size, fan, and weight.

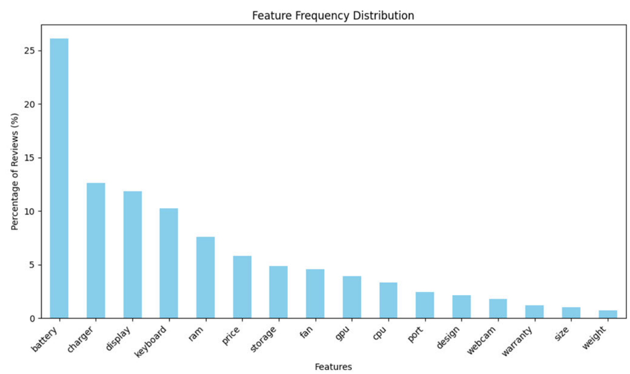

FIGURE 3. Distribution of Top 16 laptop aspects in user reviews.

Figure 3, illustrates the frequency of each aspect in the dataset. This visualization highlights the relative importance of each feature based on user discussion.

This implementation of ABSA, combined with the aspect list and sentiment analysis, provided comprehensive insights into consumer sentiment on specific laptop features, offering valuable feedback for manufacturers and marketers alike.

D. SENTIMENT ANALYSIS RESULTS

The Aspect-Based Sentiment Analysis (ABSA) revealed distinct sentiment patterns for the 16 most frequently discussed laptop features across developed and developing countries. Our analysis focused exclusively on positive and negative sentiments, excluding neutral reviews to capture more definitive consumer preferences and actionable insights.

Table 5 presents the sentiment distribution across all features, highlighting significant differences between developed and developing markets. Generally, consumers in developing countries exhibited higher satisfaction across many aspects of laptops, while those in developed countries demonstrated more critical perspectives. This pattern was particularly evident in features such as battery life and cooling efficiency, which emerged as universal concerns across both markets. Design appreciation showed a notable disparity, with 86% positive sentiment in developing countries compared to 70% in developed countries. Similarly, warranty services received significantly different responses, with developed countries showing high dissatisfaction (70% negative reviews) while developing countries maintained more balanced views.

TABLE 5. Sentiment distribution for laptop features in developed and developing countries.

ASPECT	POSITIVE REVIEWS ED[1]	NEGATIVE REVIEWS ED	POSITIVE REVIEWS ING[2]	NEGATIVE REVIEWS ING
RAM	44.06%	55.94%	63.68%	36.32%
DISPLAY	46.64%	53.36%	56.40%	43.60%
KEYBOARD	31.96%	68.04%	47.24%	52.76%
PRICE	58.42%	41.58%	69.87%	30.13%
BATTERY	29.19%	70.81%	39.40%	60.60%
STORAGE	40.05%	59.95%	48.15%	51.85%
GPU	44.13%	55.87%	63.06%	36.94%
CPU	42.04%	57.96%	65.82%	34.18%
CHARGER	12.83%	87.17%	20.41%	79.59%
WARRANTY	29.51%	70.49%	48.52%	51.48%
DESIGN	70.36%	29.64%	86.43%	13.57%
WEBCAM	25.69%	74.31%	49.29%	50.71%
PORT	33.28%	66.72%	44.26%	55.74%
SIZE	65.97%	34.03%	61.42%	38.58%
FAN	13.60%	86.40%	18.54%	81.46%
WEIGHT	53.48%	46.52%	68.59%	31.41%

1) SENTIMENT ANALYSIS RESULTS FOR DEVELOPED COUNTRIES

Analysis of developed markets reveals a clear distinction between performance-related and design-focused features, as illustrated in Figure 4. Consumers in developed countries expressed particular criticism toward performance-related elements, with RAM, GPU, and CPU receiving notably higher negative sentiments. Display quality generated mixed responses, suggesting ongoing debates about performance standards in these markets. Battery performance and charging systems emerged as significant pain points, with users frequently expressing frustration over durability and efficiency.

Despite critical views on performance aspects, developed market consumers showed appreciation for certain features. Design elements and pricing received generally positive feedback, indicating satisfaction with aesthetic qualities and perceived value. However, keyboard quality emerged as a particular concern, with users expressing dissatisfaction regarding durability and ergonomic aspects of their devices.

2) SENTIMENT ANALYSIS RESULTS FOR DEVELOPING COUNTRIES

Consumer sentiment in developing markets, as shown in Figure 5, demonstrates distinctly different priorities and expectations compared to developed regions. Performance-related features such as RAM, GPU, and CPU received notably higher positive ratings, suggesting better alignment between user expectations and product capabilities in these markets. The positive sentiment extends to price considerations, with users showing significant appreciation for devices that offer good value for money.

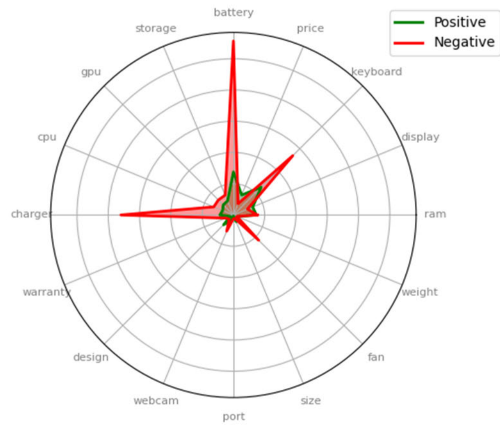

FIGURE 4. Sentiment distribution for laptop features in developed countries.

While battery performance and charging systems still garnered negative feedback in developing markets, the criticism was less severe compared to developed regions. This suggests different priority levels for these features across economic contexts. Design aspects stood out particularly positively in developing markets, with users expressing strong satisfaction with aesthetic appeal and build quality. The overall sentiment pattern indicates that developing market consumers prioritize durability, reliability, and value proposition, while maintaining more moderate expectations for cutting-edge performance features.

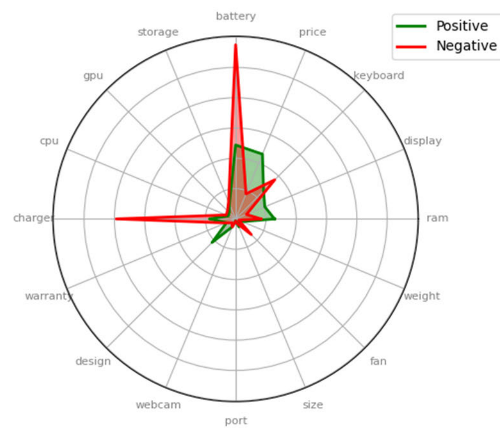

FIGURE 5. Sentiment distribution for laptop features in developing countries.

E. DELPHI PANEL

1) PROCESS OF SELECTING EXPERTS

To ensure a comprehensive and balanced perspective on laptop component satisfaction across developed and developing countries, a strategic approach was employed in selecting our expert cohort for the Delphi process. The selection parameters were designed to cover a wide range of considerations:

- Age: Experts from different age groups were included to capture diverse generational insights.
- Gender: Gender balance was prioritized to ensure a diversity of viewpoints.
- Country of Residence: Experts were selected from both developed and developing countries to reflect the study's focus.
- Job Title: Various roles within the laptop industry were considered to ensure a broad range of expertise.
- Years of Experience: Experts with significant experience in the laptop industry were prioritized.
- Field of Activity: Experts from diverse areas such as design, manufacturing, sales, and customer experience were included.

The selection process for the Delphi panel involved several rigorous steps:

1) Initial Identification: Potential experts were identified through:
   - Industry publications and tech forums
   - Recommendations from professional networks
   - Searches of professional databases and LinkedIn
2) Qualification Assessment: Each potential expert's qualifications were evaluated based on:
   - Years of experience in the laptop industry
   - Involvement in laptop design, manufacturing, or sales
   - Recognition in the field, such as awards or speaking engagements
   - Knowledge of both developed and developing markets
3) Diversity Criteria: The pool of qualified experts was filtered to ensure diversity across the aforementioned parameters (age, gender, country of residence, etc.).
4) Invitation and Confirmation: Selected experts were invited to participate in the Delphi panel through emails and LinkedIn messages. Those who accepted were provided with detailed information about the study's objectives and the Delphi process.
5) Final Panel Formation: The final panel was formed by balancing expertise across different aspects of the laptop industry while maintaining the desired diversity between developed and developing countries.

This thorough selection process aimed to create a panel capable of providing well-rounded, informed, and diverse perspectives on laptop component satisfaction and potential solutions. As a result, ten experts were meticulously chosen to participate in the Delphi process, facilitating a robust and comprehensive exploration of the research questions. Details about the experts involved in the Delphi panel are presented in Table 6.

This panel of experts represents a balanced mix of perspectives from both developed and developing countries, along with diverse expertise in various areas of the laptop industry. This ensures a comprehensive evaluation of consumer satisfaction with laptop components across different markets.

TABLE 6. Profile of the expert panel.

Age	Gender	Country	Developed / Developing	Job Title	Years of Experience
48	Male	Japan	Developed	Laptop Industrial Designer	19
33	Female	USA	Developed	Laptop Quality Assurance Specialist	9
42	Female	UK	Developed	Laptop Hardware Engineer	15
36	Male	Spain	Developed	Senior Laptop Sales Specialist	9
55	Female	Germany	Developed	Senior Laptop Product Manager	20
49	Male	Brazil	Developing	E-commerce Laptop Sales Coordinator	12
51	Female	Vietnam	Developing	Laptop Manufacturing Process Engineer	11
45	Male	Egypt	Developing	Regional Laptop Sales Manager	15
36	Male	UAE	Developing	Laptop Sales Analytics Manager	14
38	Female	Serbia	Developing	Laptop Customer Experience Specialist	12

2) EXTRACTION OF KEY SOLUTIONS

Phase 1 (Initial Proposal of Solutions): Initially, the identified components were presented to the experts, who were then asked to propose potential solutions for improving user satisfaction for each component, considering the specific needs of developed and developing countries. Experts from developed countries only proposed solutions for their markets, while experts from developing countries focused on solutions for their respective markets. This stage allowed for the generation of a wide range of possible solutions, leveraging the diverse expertise of the panel. After collecting the questionnaires and compiling the data, approximately 40 to 45 solutions were extracted for each component. By consolidating these solutions and eliminating redundant suggestions, a refined list of approximately 15 to 20 unique solutions for each component was developed.

Phase 2 (Rating the Solutions): In the second stage, all proposed solutions were compiled into a list. Experts were then asked to rate each solution using a Likert scale, where 5 indicated strong agreement, 4 agreement, 3 neutrality, 2 disagreement, and 1 strong disagreement. The experts rated each solution using the Likert scale. Experts only rated solutions for their respective country categories; developed country experts rated solutions for developed markets while developing country experts rated solutions for developing markets. At the end of this process, the questionnaires were collected, and the score for each solution was calculated.

Phase 3 (Final Review and Refinement): In the final stage, both the list of components and the corresponding solutions, along with their Likert scale ratings, were provided to the experts for a final review. Experts were invited to make any necessary revisions or provide additional comments to refine the solutions further. This process aimed to achieve a consensus on the most viable solutions for each component in both developed and developing countries. The Delphi method resulted in the identification and prioritization of several key solutions for each laptop component.

TABLE 7. Top solutions for laptop components by country classification: Developed vs. Developing.

Feature	Country	Solution
Charger	Developed Countries	➢ Universal USB-C Charging: Implement USB-C charging across all laptop models, promoting compatibility and reducing the need for multiple chargers. ➢ GaN Technology Integration: Utilize Gallium Nitride technology in charger design, resulting in more compact and efficient power adapters. ➢ Multi-Device Charging Capability: Develop chargers with multiple ports, enabling simultaneous charging of laptops and other devices for increased convenience.
	Developing Countries	➢ Wide Input Voltage Range: Design chargers capable of handling varied voltage inputs, addressing the challenge of unstable power grids in developing regions. ➢ Built-in Surge Protection: Incorporate surge protection mechanisms into chargers, safeguarding devices against power fluctuations common in developing areas. ➢ Solar-Powered Charging Options: Offer solar charging capabilities or compatible power banks, providing alternative power sources in areas with unreliable electricity.
Fan	Developed Countries	➢ Advanced Airflow Design: Develop fan systems with improved airflow dynamics and noise reduction technologies for enhanced cooling efficiency. ➢ AI-Driven Fan Control: Implement intelligent fan control systems that optimize cooling performance and noise levels based on real-time usage patterns. ➢ Alternative Cooling Technologies: Explore and integrate advanced cooling solutions such as vapor chambers or liquid cooling systems for high-performance laptops.
	Developing Countries	➢ Dust-Resistant Fan Design: Incorporate dust-resistant features in fan systems to improve longevity and maintain cooling performance in dusty environments. ➢ Modular Fan Systems: Design easily accessible and replaceable fan modules, allowing for simpler maintenance and repairs without specialized tools.
Battery	Developed Countries	➢ User-Replaceable Batteries: Design laptops with easily accessible and replaceable batteries, extending device lifespan and improving repairability. ➢ Fast and Wireless Charging: Integrate rapid charging technologies and wireless charging capabilities for enhanced user convenience.
	Developing Countries	➢ High-Temperature Optimized Batteries: Develop battery technologies specifically designed to maintain performance and longevity in hot climates. ➢ Increased Battery Capacity: Offer higher capacity batteries as standard to address power availability concerns in regions with unreliable electricity.
Webcam	Developed Countries	➢ AI-Enhanced Image Processing: Integrate artificial intelligence algorithms for improved video quality, including features like automatic background blur. ➢ Physical Privacy Shutters: Implement built-in camera covers, addressing privacy concerns and providing users with control over camera access. ➢ Low-Light Performance Optimization: Develop advanced sensor and software technologies to enhance webcam performance in poor lighting conditions.
Warranty	Developed Countries	➢ AI-Powered Diagnostics: Implement intelligent diagnostic tools for quicker and more accurate identification of hardware and software issues. ➢ Easily Replaceable Components: Design laptops with modular, easily swappable components to streamline warranty repairs and reduce downtime.
Port	Developing Countries	➢ Legacy Port Inclusion: Maintain compatibility with older equipment by including legacy ports like VGA, addressing the prevalence of older technologies. ➢ USB Port Variety: Offer a mix of USB-A and USB-C ports, balancing compatibility with both newer and older peripheral devices. ➢ Port Protection: Incorporate dust covers for ports to shield against environmental factors and extend the lifespan of connection interfaces.
Keyboard	Developing Countries	➢ Modular Keyboard Design: Implement easily replaceable keyboard modules, facilitating cost-effective repairs and maintenance. ➢ Durable Key Switches: Utilize robust key switch technology designed to withstand dusty environments and heavy usage patterns. ➢ Non-Backlit Keyboards: Opt for non-backlit keyboards to reduce power consumption and component costs in budget-friendly models.

Table 7, shows the top 2 to 3 solutions for each component, separated by developed and developing countries. It is worth mentioning that to avoid making the article too long, only the 5 components with the highest levels of dissatisfaction in each category have been examined in the table. These components for developed countries are, in order: charger, fan, webcam, battery, and warranty. For developing countries, they are fans, chargers, batteries, ports, and keyboards.

Figure 6 presents a visual summary of the key challenges and expert-recommended solutions for laptop components, differentiated between developed and developing countries. This graphical representation encapsulates the findings from the Delphi method, highlighting the top priorities

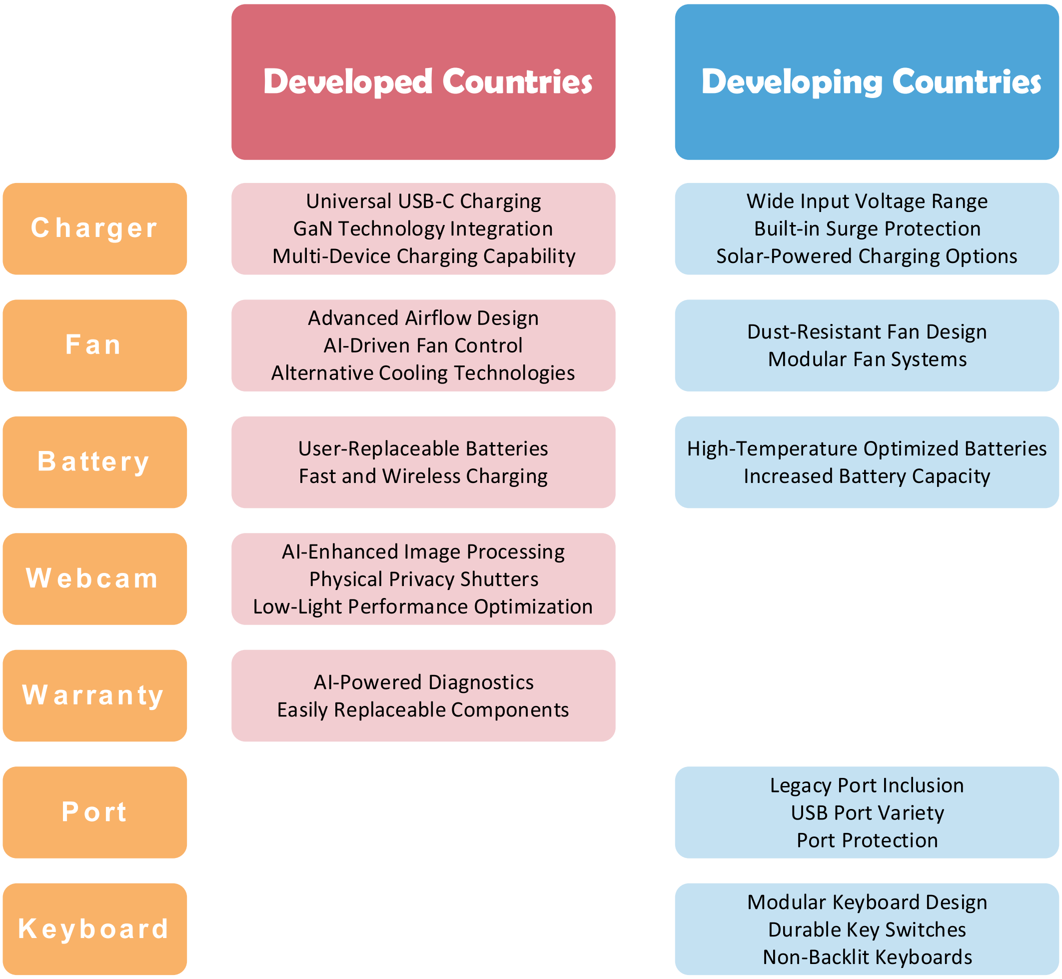

FIGURE 6. **Visual summary of the key challenges and expert-recommended.**

and proposed innovations for each component category. The image effectively illustrates the divergent focus areas between developed and developing nations. For instance, while developed countries prioritize advanced technologies like AI-driven systems and alternative cooling methods, developing countries' solutions are more oriented towards durability, adaptability to harsh environmental conditions, and compatibility with existing infrastructure.

This comparative visualization underscores the importance of tailored approaches in addressing laptop design and functionality across different economic contexts. It provides a clear, at-a-glance overview of how manufacturers might strategically adapt their product development to meet the specific needs and challenges of diverse global markets.

V. DISCUSSION

The analysis of laptop user sentiments across developed and developing countries reveals significant insights into consumer preferences, expectations, and pain points. This research set out to answer four key questions, which can now be addressed based on the findings.

1. What are users' opinions on social media about different laptop features, according to developed and developing countries? How do these views differ?

The sentiment analysis results demonstrate clear differences in user opinions between developed and developing countries. Generally, consumers in developing countries exhibited higher satisfaction across many laptop aspects, while those in developed countries tended to be more critical. This disparity suggests that consumers in developed countries have higher expectations for laptop performance and features, possibly due to greater exposure to advanced technologies and more competitive markets.

Specific features like battery life and fan performance were universally problematic, with consistently negative reviews in both regions. This indicates that these are critical areas for improvement regardless of the market. Conversely, design was overwhelmingly positively received in developing countries (86% positive) compared to developed countries (70% positive), suggesting that aesthetic appeal and build quality may be more appreciated in developing markets.

2. What are the priorities of laptop users in developed countries?

The analysis reveals that users in developed countries prioritize high performance, long battery life, and efficient cooling systems. They are particularly critical of chargers, fans, webcams, batteries, and warranty services. The high expectations for these features likely stem from the fast-paced, technology-driven lifestyles common in developed nations. Users in these countries expect their laptops to keep up with demanding workloads, maintain long-lasting performance, and provide seamless integration with their digital ecosystems.

3. What are the priorities of laptop users in developing countries?

In developing countries, users prioritize affordability, durability, and reliability. While they share concerns about fans, chargers, and batteries with their counterparts in developed countries, they also place significant importance on ports and keyboards. This focus likely reflects the need for versatility and longevity in markets where replacing a laptop might be a more significant financial burden. The positive sentiment towards price in developing countries underscores the importance of value for money in these markets.

4. What set of actions should laptop manufacturing companies take to address the opinions and needs of consumers in developed and developing countries?

The research findings suggest that laptop manufacturers should adopt a differentiated approach to product development and marketing for developed and developing markets. For developed countries, focus should be on cutting-edge performance, advanced cooling solutions, high-quality webcams, and comprehensive warranty services. For developing countries, emphasis should be on durable designs, versatile port options, and features that enhance longevity and reliability.

A. MANAGERIAL INSIGHTS AND IMPLEMENTATION

Based on the research findings, the following recommendations are proposed for laptop manufacturing companies:

1. **Differentiated Product Lines**: Develop distinct product lines tailored to the specific needs of developed and developing markets. For developed countries, focus on high-performance models with advanced features. For developing countries, prioritize durable, versatile models with a strong price-to-performance ratio.
2. **Universal Charger Solutions**: Implement USB-C charging across all models to address charger-related dissatisfaction in both markets. For developing countries, incorporate surge protection and wide input voltage range to tackle power grid instability issues.
3. **Cooling System Innovations**: Invest in advanced cooling technologies for developed markets, such as AI-driven fan control and alternative cooling solutions. For developing countries, focus on dust-resistant and easily maintainable fan systems.
4. **Battery Improvements**: Develop high-capacity, user-replaceable batteries for developed markets. For developing countries, focus on batteries optimized for high-temperature environments and longer life spans.
5. **Webcam Enhancements**: For developed markets, integrate AI-enhanced image processing and physical privacy shutters. While not a top concern in developing countries, ensuring adequate webcam quality could be a differentiator.
6. **Warranty and Support**: Implement AI-powered diagnostics and design easily replaceable components to improve warranty services in developed countries. For developing countries, focus on establishing robust local repair networks and offering extended warranty options.
7. **Port Strategy**: For developing countries, maintain a mix of legacy and modern ports to ensure compatibility with a wide range of devices. Consider including port protection features to enhance durability.
8. **Keyboard Design**: In developing countries, focus on modular, durable keyboard designs that can withstand harsh environments and are easy to replace or repair.
9. **Marketing Strategy**: Tailor marketing messages to reflect the priorities of each market. Emphasize cutting-edge technology and performance in developed countries, while focusing on durability, versatility, and value in developing countries.
10. **Continuous Feedback Loop**: Implement systems to continuously monitor and analyze user sentiments across different markets, allowing for rapid adaptation to changing consumer needs and preferences.

B. PRACTICAL APPLICATIONS

Our research findings have significant practical applications across multiple domains, extending beyond theoretical contributions to provide tangible value in various industry contexts.

In product development, our methodology enables manufacturers to implement real-time feature prioritization based on market-specific sentiment analysis. This approach allows companies to adapt their design processes continuously, incorporating regional user feedback to create products that better meet local needs. For instance, manufacturers can develop customized testing protocols that reflect the actual usage conditions in different markets, leading to more reliable and market-appropriate products. The sentiment analysis framework we've developed helps companies identify which features require enhancement or modification for specific markets, enabling more efficient resource allocation in the development process.

The manufacturing and quality control sector benefits particularly from our findings through the implementation of market-specific standards and procedures. Our research enables companies to adapt their manufacturing processes to regional requirements while maintaining global quality standards. For example, manufacturers can develop distinct durability testing procedures that reflect the environmental challenges of developing markets, while focusing on performance optimization for developed markets. This nuanced approach to manufacturing and quality control ensures that products not only meet basic requirements but excel in their intended market contexts.

In the marketing and sales domain, our research provides a foundation for sophisticated, data-driven market segmentation strategies. Companies can develop region-specific value propositions based on our sentiment analysis findings, creating marketing messages that resonate more effectively with local consumers. This targeted approach extends to pricing strategies, allowing companies to optimize their market positioning while maintaining profitability across different economic contexts.

The customer support sector can leverage our findings to design more effective regional support networks and warranty programs. Our research indicates how companies can tailor their support services to match local expectations and infrastructure limitations. This includes developing market-specific warranty programs that address the primary concerns of users in different regions while remaining economically viable for the manufacturer.

From a technology application perspective, our sentiment analysis methodology provides a framework for developing market-specific analysis models that can be integrated into existing business intelligence systems. Companies can implement real-time sentiment monitoring systems that account for both linguistic and cultural nuances, enabling more accurate interpretation of customer feedback across different markets.

In terms of business intelligence, our research methodology offers a comprehensive framework for market analysis and decision support. Companies can use our approach to track consumer preferences in real-time, predict market trends, and assess regional market opportunities more accurately. This enables more informed decision-making in product development, market entry strategies, and resource allocation.

For the research community, our work provides a robust framework for studying technology adoption across different economic contexts. The methodology we've developed can be adapted for various types of consumer technology research, offering a template for combining quantitative sentiment analysis with qualitative expert insights. This approach is particularly valuable for researchers studying how economic and cultural factors influence technology preferences and adoption patterns.

C. LIMITATIONS AND FUTURE RESEARCH

While this research provides valuable insights into laptop user sentiments across developed and developing countries, several limitations should be acknowledged:

- Data Source: The study relied primarily on social media data, which may not fully represent all laptop users, particularly those less active on these platforms.
- Language Limitations: Despite using multiple languages, the study may not capture sentiments from all linguistic groups, potentially missing important regional variations.
- Temporal Scope: The research covered a specific time frame and may not account for long-term trends or sudden shifts in consumer preferences due to external factors.
- Expert Panel Size: The Delphi panel, while diverse, was limited to ten experts, which may not capture the full range of industry perspectives.

Future research could address these limitations and expand on the findings:

- Multi-Source Data: Incorporate data from diverse sources such as product reviews on e-commerce platforms, customer support logs, and traditional surveys to provide a more comprehensive view of user sentiments.
- Longitudinal Study: Conduct a long-term study to track changes in user sentiments over time, potentially revealing evolving trends in laptop preferences.
- Feature Interaction Analysis: Investigate how different laptop features interact to influence overall user satisfaction, which could provide insights for more holistic product development strategies.
- Economic Impact Study: Examine how economic factors such as GDP, average income, and technology adoption rates in different countries correlate with laptop preferences and sentiments.
- User Segment Analysis: Conduct a more granular analysis of user segments within developed and developing countries, considering factors such as age, profession, and primary use case.
- Competitive Landscape: Expand the research to include brand-specific sentiments, allowing for a comparative analysis of how different manufacturers are perceived in various markets.

By addressing these areas, future research can provide even more nuanced and actionable insights for the laptop industry, enabling manufacturers to better serve the diverse needs of global consumers.

VI. CONCLUSION

This comprehensive study on laptop user sentiments across developed and developing countries has yielded valuable insights into the nuanced preferences, expectations, and pain points of consumers in different economic contexts. By leveraging aspect-based sentiment analysis on a large corpus of social media data and incorporating expert opinions through a Delphi panel, this research has uncovered significant distinctions in how users perceive and prioritize various laptop features.

The findings reveal that while consumers in developing countries generally express higher satisfaction with laptop features, those in developed countries tend to be more critical, particularly regarding performance-related aspects. This disparity underscores the importance of tailored product development and marketing strategies for different global markets. Universal concerns, such as battery life and cooling efficiency, emerged as critical areas for improvement across all markets, highlighting the need for continued innovation in these domains.

The research also illuminates the specific priorities of users in different economic contexts. In developed countries, high performance, long battery life, and efficient cooling systems are paramount, reflecting the demands of technology-driven lifestyles. Conversely, users in developing countries prioritize affordability, durability, and reliability, emphasizing the need for laptops that offer value for money and can withstand challenging environmental conditions.

These insights lead to a set of actionable recommendations for laptop manufacturers. These include developing differentiated product lines, implementing universal charging solutions, investing in cooling system innovations, and enhancing warranty services. The study also emphasizes the importance of continuous monitoring of user sentiments to adapt to evolving consumer needs rapidly.

While this research provides a solid foundation for understanding global laptop user sentiments, it also opens avenues for future research. Longitudinal studies, more granular user segment analyses, and investigations into the economic factors influencing laptop preferences could further enrich our understanding of this dynamic market.

In conclusion, this study contributes significantly to the field by offering a data-driven approach to understanding and addressing the diverse needs of laptop users worldwide. By highlighting the importance of market-specific strategies and continuous innovation, it provides valuable guidance for laptop manufacturers aiming to enhance user satisfaction and maintain competitiveness in an increasingly globalized market. As technology continues to evolve and user expectations shift, the insights gained from this research will serve as a crucial reference point for future product development and marketing strategies in the laptop industry.

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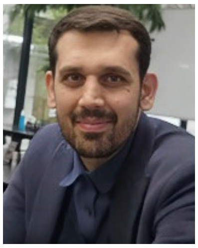

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