KUPAS SENI
Jurnal Seni dan Pendidikan Seni
ISSN 2289-4640 • eISSN 0127-9688

Understanding Language and Culture Through Sentiment Analysis: A Conceptual Framework

Memahami Bahasa dan Budaya melalui Analisis Sentimen: Satu Kerangka Konseptual

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ARTICLE HISTORY
Received: 10th December 2025
Revised: 13rd Mac 2026
Accepted: 23rd April 2026
Published: 27th April 2026

KEYWORDS
Language and Culture
Sentiment Analysis
Conceptual Framework
Cross-Cultural Communication
Linguistic Approaches

ABSTRACT - This article presents a conceptual framework that facilitates understanding of how language and culture influence emotional expressions in the online world. Although sentiment analysis is a popular instrument for data analysis, the majority of computational studies focus on the algorithm's accuracy and thus ignore the cultural and linguistic aspects of the data. This paper merges the linguistic, cultural, and computational elements to demonstrate that language, culture, and emotions are interconnected and form a triangle. The proposed framework consists of three layers: the Language Layer (lexical and discourse features), the Culture Layer (norms, values, and communication styles), and the Sentiment Layer (polarity, emotional tone, and intensity). These stages are always interacting with each other, culture shapes language, and both language and culture determine the way emotions are expressed and recognised. By integrating these different aspects, the research constitutes a richer, interdisciplinary approach to sentiment analysis in different cultural contexts. The presented framework is an interdisciplinary one and may serve as a guide in the fields of linguistics, intercultural communication, education, and digital marketing, where the comprehension of the emotional expressions of different cultures is of utmost significance.

https://doi.org/10.37134/kupasseni.vol14.sp.11.2026

INTRODUCTION

The digital era has made people to be not only geographically, but also culturally separated. Global platforms like social media enable individuals to present their thoughts, feelings, and ideas every day. Nevertheless, the cultural and linguistic differences of the individuals involved in the interaction influence their perception of the message as well as its delivery. Acknowledging this interplay of language, culture, and emotion has become an essential part of communication and technology research.

Sentiment analysis is a part of natural language processing (NLP) that is primarily concerned with identifying the feeling and opinion of the author in the given text. The use of transformer-based models such as BERT and RoBERTa has led to the dramatic increase of the correctness of sentiment detection (Cambria et al., 2022; Semary et al., 2023). Technological advances, notwithstanding, a great number of studies remain indifferent to linguistic and cultural factors that affect the communication of emotions. According to Hofstede (2011) and Hall (1976), language serves as a mirror to the typical cultural and social values of the community. The absence of this recognition in sentiment frameworks makes them have a high possibility of constituting biased or partial results.

This paper fills this gap by presenting a conceptual framework which connects linguistic, cultural, and computational views in sentiment analysis. It shows how words, grammar, and speech are related to cultural values and affect emotional expression. The combination of linguistic and cultural theories with computational insights results in the framework that takes into consideration not only the aspects of language, but also the social structures of different societies, thus is more comprehensive and accommodating in terms of sentiment across languages and communities.

Theoretically, this paper serves as a bridge among linguistics, communication, and artificial intelligence disciplines by stressing the amalgamation of theory and technology. On the ground, it delivers cross, cultural communicators, and digital marketing practitioners' innovative ways of work, as well as attractive learning possibilities in their field where the mastery of the emotional tone precipitate the success of their activities (Anggia & Sumi, 2024; Huang, 2024).

LITERATURE REVIEW

2.1. Advances in Sentiment Analysis

The field of sentiment analysis has shifted from lexicon, based methods to deep learning frameworks that can handle vast amounts of natural language data. In particular, transformer, based frameworks like BERT and RoBERTa have been credited with a major leap in performance by being able to understand the meaning of the text in the given context (Cambria et al., 2022). The combination of several neural networks to form one hybrid framework provides an even higher level of precision in the output (Alharbi & Alshahrani, 2025). However, a top, notch technical performance does not necessarily guarantee a fair or culturally sensitive system. At this point, the frameworks have limited capabilities to decode references, idioms, and pragmatic hints that are culture, based (Li et al., 2025).

2.2. Language and Emotional Expression

Language is more than just a means of communication; it is a way of showing one's attitudes and emotions. According to The Appraisal Theory (Martin & White, 2005), it is mainly through the use of evaluative language that speakers and writers communicate their sentiments and judgements. The same way, Brown and Levinson's (1987) Politeness Theory emphasizes the role of harmony, maintaining uses of tone, mitigation, and indirectness in social interactions. These and other linguistic techniques differ substantially from one culture to another. For instance, the English expression of dissatisfaction that is considered direct could be polite and indirect in Japanese or Malay. The overlooking of such linguistic subtleties may cause significant misinterpretations of sentiment analysis (Lei & Liu, 2022; Zeng, Zhou, & Liu, 2022).

https://doi.org/10.37134/kupasseni.vol14.sp.11.2026

2.3. Cultural Dimensions of Sentiment

Communication of emotions is highly dependent on culture. Hofstede (2010), in his model of cultural dimensions, identifies individualistic and collectivist societies as two different entities, resulting in different ways of conveying such emotions as anger or gratitude. Similarly, Hall's (1976) theory of high, and low, context communication states that those cultures, which are high, context, mostly use implicit cues, while those, which are low, context, opt for explicit expression. Recent developments in culturally adaptive frameworks, examples of which include multilingual transformers like XLM and multimodal frameworks like RSA, show that the inclusion of cultural context leads to a major improvement in the accuracy of sentiment analysis. Such frameworks can more effectively grasp subtle emotional expressions in different languages and cultures, thus lowering the rate of misclassification and making the results more understandable (Chen et al., 2025; Zeng et al., 2022). The point here is that the expression of sentiment is not a universal language but is culture, dependent.

2.4. Existing Framework

An exemplary case is the GSAF: An ML, Based Sentiment Analytics Framework created by Mohammed et al. (2025), which combines machine learning and natural language processing to detect public sentiment in real, time across social media platforms. GSAF not only identifies emotional trends, like joy, anger, and trust, related to pressing societal issues but also displays them spatially (e.g., through U.S. state, wise maps) and facilitates decision, making in sectors like policy, marketing, and public discourse.

This system is a great fit for current research as it essentially bridges the gap between text data and public values, thereby providing a scalable framework for sentiment analysis. Nevertheless, while GSAF is concerned with vast, scale social media data and emotional metrics, this research takes the concept further by including intricate linguistic and cultural aspects such as lexical choice, discourse norms, and cross, cultural communication patterns, hence increasing the interpretive capacity of sentiment analytics.

2.5. Research Gap

Despite the rapid pace of technical advances in sentiment analysis, research in this field still turns a blind eye to the integration of linguistic and cultural theories. The majority of the studies emphasize the optimization of the framework at the expense of understanding of the context. The resulting systems are great performers in English but not in other languages or cultural contexts (Amos, 2024). In this way, the need for a more inclusive conceptual framework that reconciles the computational aspect with the cultural and linguistic one remains unfulfilled.

THEORETICAL FOUNDATION

The conceptual framework of the proposed system is fundamentally based on three core theoretical sources: language theories, cultural models, and computer science perspectives.

3.1. Linguistic Theories

According to Appraisal Framework (Martin & White, 2005), the main features of language to express emotions and evaluations are identified in three key areas, attitude, engagement, and graduation. Politeness Theory (Brown & Levinson, 1987) supports this by giving examples of how the speakers change their language to keep social relations intact. Both theories support the concept that language is inseparable from its social and cultural environments. These theories, when used in conjunction with computational analysis, help to decipher the emotional tones in a multilingual dataset.

3.2. Cultural Models

Hofstede's (2011) and Hall's (1976) theories provide the rationale for the relationships between culture and communication. As an example, the members of collectivist societies typically communicate in a moderate way so as not to disturb the harmony of the group whereas people of individualistic cultures openly show their feelings and expect the same of others. These differences explain the fact that same

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words or phrases can have different emotional strengths in different cultures. Furthermore, several recent investigations reveal that the use of cultural knowledge in sentiment analysis is a way to reduce bias and enhance the correctness of understanding. Frameworks that involve cultural context i.e. use of multilingual and cross, cultural datasets or culturally adaptive architectures show better results in generalizing subtle emotional expressions in different groups of people (Chen et al., 2025; Li et al., 2025).

3.3. Computational Foundations

Computational sentiment analysis is done with the help of automatic learning techniques that are able to pinpoint the texts' emotional expressions. Sentiment analysis has been enhanced by transformer, based frameworks such as BERT and RoBERTa which are able to comprehend the meaning of words in the context. In contrast to traditional lexicon, based methods which depend on fixed word lists, transformers employ deep learning to detect even the most subtle emotional cues, idioms, and cultural expressions. According to Dubey, Dubey, and Bokoro (2025), sarcasm, negation, and ambiguity are the problems with which many sentiment systems are still wresting, while these issues are better handled by context, aware frameworks. The finding of Bashiri and Naderi (2024) is in line with this, too, that transformers beat the older methods in different languages.

However, these systems are still very limited when it comes to the detection of ironic statements and the understanding of indirectness, as well as other culturally specific hints. Therefore, the interplay of computational power with linguistic and cultural knowledge is necessary if one wants to create sentiment frameworks that are not only correct but also cover the entire scope of human experience (Bashiri & Naderi, 2024).

PROPOSED CONCEPTUAL FRAMEWORK

The proposed framework blends the three perspectives: linguistic, cultural, and computational, to elaborate on the communication of emotion through language. It sees affect as the consequence of the ongoing interaction of three interdependent layers: Language, Culture, and Sentiment. Each layer has variables that influence each other not only through direct relationships but also through indirect ones. The framework is capable of being a qualitative interpretative and quantitative modelling tool for emotional expression.

4.1. Language Layer

The Language Layer characterises the linguistic structures by which speakers or writers show their attitude and emotion. The layer is described as including words, syntax, and the organisation of the discourse. The variables of this layer may be the intensity of the adjective, the usage of evaluative verbs, the choice of pronouns, and the complexity of the sentence. For example, the first, person pronouns are used frequently to denote personal engagement, whereas hedging expressions, like perhaps or somewhat, indicate that the emotional intensity is toned down. The layer also considers that the spoken language may incorporate features such as the politeness strategies and modal verbs that help to lessen the emotional impact.

4.2. Culture Layer

The Culture Layer aims to explain those social and cultural factors that influence linguistic behaviour. The factors depicted by the layer are shared norms, communication styles, and value systems determining not only the manner of expression of emotion but also its suppression. Variables are directness levels, collectivism or individualism preference, and communicative orientation, high or low, context. In many Asian societies, when delivering criticism, one would use indirect expressions like the service could improve in order to be polite, while in the Western cultures the explicitness in the statements is preferred (Effendi, 2021). Thus, the Culture Layer, on the one hand, negotiates the ways linguistic forms are used and on the other hand, characteristics of sentiment are influenced in terms of both strength and style as well.

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4.3. Sentiment Layer

The Sentiment Layer is the output of the emotional system that is attained with the interaction of language and culture. The elements included here are polarity (positive, negative, or neutral), emotional tone, and intensity. In a quantitative way, sentiment is reflected through computational scores obtained from lexicon or transformer frameworks. Nevertheless, this framework perceives those scores as being filtered through the lens of linguistic and cultural context in order to keep the understanding comprehensive. If an indirect language is moderate in polarity and is accompanied by the cultural norms, this, for instance, still may be a case of strong dissatisfaction if in that culture explicit negativity is discouraged.

4.4. Illustrative Example

The framework as illustrated in Figure 1 is suitable for application in a multilingual customer service scenario. An airline, for instance, might be gathering feedback from passengers who speak different languages. The analysts first look at the lexical and syntactic features of the reviewers' texts (Language Layer). Then, they analyse the cultural norms of the expression to see if the patterns match the norms (Culture Layer). Lastly, they utilize sentiment analysis tools to determine overall polarity and emotional tone (Sentiment Layer). Inter, layer comparison of results helps to avoid cases where polite criticism is judged as neutral sentiment and also brings out the role of culture in shaping the linguistic expression.
Mathematical Representation

The interaction among layers can be expressed through a simplified functional framework as noted in equation (1):

$$S = f(L, C) \qquad \text{(eq1)}$$

where S represents the sentiment outcome, L denotes linguistic variables, and C denotes cultural parameters. Expanding the relationship as shown in equation (2):

$$S_i = \alpha + \beta_1 L_i + \beta_2 C_i + \beta_3 (L_i \times C_i) + \varepsilon_i \qquad \text{(eq2)}$$

Here S_i is the sentiment intensity for observation i, L_i includes linguistic indicators (e.g., adjective polarity, modality frequency), C_i represents cultural indicators (e.g., directness index, collectivism score), α is a constant, and ε_i is the error term. The interaction term $L_i \times C_i$ captures how culture moderates the effect of language on sentiment. In practical application, coefficients $(\beta_1, \beta_2, \beta_3)$ may be estimated through regression or structural-equation framework using coded textual data.

This mathematical structure does not replace qualitative interpretation but complements it. It provides an analytical outline for researchers to operationalise the three-layer framework quantitatively, demonstrating that sentiment emerges from both linguistic expression and cultural mediation.

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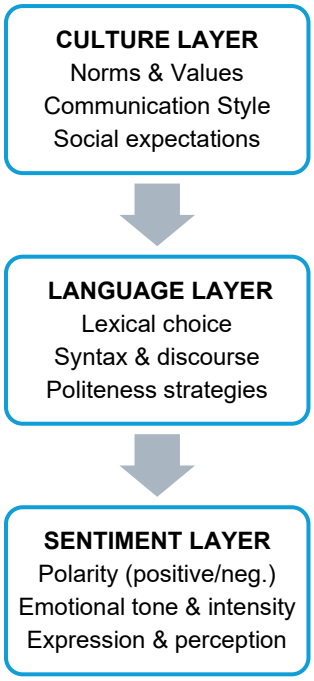

Figure 1. Conceptual Framework:
Interaction Between Language, Culture, and Sentiment

APPLICATIONS OF THE FRAMEWORK

Such a framework as proposed can be a great help in understanding and interpreting cross, cultural communication. The main point is how different are the ways of expressing emotions in different societies; knowing this, communicators can lessen the number of misunderstandings and understand the messages they get with higher accuracy. As an example, emotional restraint in East Asian cultures must not be interpreted as lack of emotions but as a cultural norm for keeping harmony (Hofstede, 2010). Understanding of this may lead not only to the interpersonal relationships' quality but also communication's competence on the global level.

In the fields of marketing and business, the framework helps the enterprises to realize the emotional states of their customers more vividly. Being aware of cultural and linguistic differences allows marketers to formulate the messages that target the audience get engaged in more effectively. The company sponsored campaigns will not only reflect the local values but also the people's mood, hence brand communication will be seen as authentic and respectful (Lou & Chen, 2025; Mohamed, 2025). Consequently, consumer loyalty is being fortified, and customer satisfaction is increasing in different markets.

The framework serves to introduce ethics, politeness, and intercultural communication issues in the educational sector. Turning to linguistic and cultural knowledge, teachers may educate students on the various ways of emotional expression in different languages. The learners' communication abilities grow along with their cultural awareness and empathy (Jiang, Liu, Guo, & Wang, 2022). This language learning approach that combines theory and practice not only deepens the learning of the language but also prepares the students with the required skills for global interaction.

The above framework is a great asset for digital world as well when it comes to analysing social media and internet discussions. Understanding of language and culture variation allows for a much more accurate interpretation of online sentiment trends (Li, Zhang, & Zhou, 2025). Besides that, it facilitates the detection of newly arising public opinions, emotional tones, and societal reactions. For scientists, it unveils the intricate process of expression of feelings and construction of meaning in the diverse online communities (Li, Zhang, & Zhou, 2023).

The following table 1, recommends several tools or methods that can be used for each layer.

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Table 1. Tools and Methods

Purpose	Example Tools / Methods	Description
CULTURAL LAYER		
Cultural context & norms analysis	LIWC (Linguistic Inquiry and Word Count) (Cela et al.,2024)	Analyzes texts for psychological and cultural dimensions (e.g., collectivism vs. individualism, formal vs. informal tone).
Cross-cultural communication analysis	Hofstede Insights framework, Intercultural Development Inventory (IDI)	Not software, but frameworks to interpret cultural behavior and norms in language use.
Discourse & pragmatic analysis	NVivo, Atlas.ti	Qualitative coding tools for identifying cultural values, norms, or social expectations in text data.
Topic modeling for cultural themes	LDA (Latent Dirichlet Allocation) via Python's gensim	Can uncover recurring themes or cultural topics in large text datasets.
Sociolinguistic analysis	Python + spaCy + Sociolinguistic lexicons	Used to detect patterns of politeness, honorifics, and cultural phrasing across groups.
LANGUAGE LAYER		
Lexical & syntactic analysis (Rajik, 2025)	spaCy, Stanza, NLTK	Perform tokenization, part-of-speech tagging, and dependency parsing to analyze grammar and lexical choice.
Discourse structure analysis	Discourse parser (e.g., Penn Discourse Treebank tools)	Identifies relations like cause, contrast, and elaboration in text.
Stylistic analysis	TextBlob, Coh-Metrix	Evaluates text coherence, complexity, and linguistic style.
Word embeddings	Word2Vec, GloVe, BERT embeddings	Capture lexical semantics and contextual meaning differences.
SENTIMENT LAYER		
Sentiment classification	VADER, TextBlob, SentiWordNet, Transformers (BERT, RoBERTa) (Barik & et al., 2024)	Detects positive, neutral, or negative sentiment polarity.
Emotion detection	NRC Emotion Lexicon, GoEmotions (Google dataset), DeepMoji	Identifies emotions like joy, anger, fear, sadness, etc.
Intensity measurement	VADER compound scores, Affect intensity lexicons	Measures how strong the emotion or opinion is.
Aspect-based sentiment analysis (ABSA)	PyABSA, BERT-based ABSA models	Links specific aspects (e.g., "food quality") to sentiment.

FUTURE DIRECTIONS

Future researchers should think of expanding the worldwide reception that would be open to different societies, a wider scale of different languages and cultures. It is to say, that the greatest part of the models works with English only, which makes their influence low in the world. It is known that the understanding of the emotional component would be considerably improved if it could be switched from the monolingual to the multilingual frameworks based on numerous datasets and not only less, researched languages (Li et al., 2025; Chen et al., 2025). Thereby the analysis of emotions would maintain that it carries the least amount of linguistic bias as different cultural contexts are considered.

The other new aspect of a future work could be multimodal sentiment analysis. The day, to day conversation may also be present in images, emojis, and the like, besides text, and that is what today communication is about. Thus, scholars can unveil the emotional content with a higher degree of accuracy (Cambria et al., 2022). This kind of research work mirrors the real situation of the digital world, where people even more so than before use multimodal ways to show their feelings which in turn gives us an accurate and complete analysis of online communication.

One of the things that can be done to make sentiment analysis better and get rid of the bias in a study is to lessen cultural bias. The idea that training data has a lot of bias might set the study to give false or

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unfair results, especially in cross, cultural situations (Yang et al., 2025). In order to get to a better point as far as fairness is concerned, scientists must be selective in their datasets and use different methods for learning. As a result, it will be easier for them to accurately address the emotional states of the people irrespective of where they come from.

Collaboration is the key factor that can lever future works' breakthroughs between linguists, cultural experts, and computer scientists. In fact, every field has its own treasure of knowledge, linguistics helps understanding the meaning, cultural studies point at the social context, and computer science supplies the analytical tools (Lei & Liu, 2022; Cambria et al., 2022). The collaboration among these experts will drive cutting-edge advancements in sentiment analysis, resulting in technologies that are not only technically robust but also culturally sensitive.

CONCLUSION

By proposing a conceptual framework that interrelates language, culture, and sentiment to exemplify how emotion is communicated, the study initially moves beyond the initial framework. The framework sees sentiment not only as a computational output but as a result of a continuous interaction between linguistic structure and cultural context. The framework, by merging viewpoints from linguistics, cultural theory, and computational science, serves as a well, rounded basis for exploring emotional meaning.

Unlike present sentiment analysis frameworks which mainly focus on data processing accuracy or framework architecture (Verma et al., 2023), the suggested framework broadens the scope to include human and contextual variables. The prevailing frameworks mostly depend on word polarity and machine learning precision. They usually consider language as neutral data whereas socially and culturally they are a system. On the other hand, the current framework positions culture and language not just as the environment but as the building blocks of sentiment. It acknowledges the fact that a particular lexical item can have different emotional intensities depending on the cultural norms of directness, politeness, or restraint.

The culturally informed framework also differs in terms of its layers. The Language Layer captures the surface structure of emotion through vocabulary and syntax. The Culture Layer provides interpretive depth by connecting these linguistic forms to shared beliefs and communicative expectations. The Sentiment Layer then combines both to generate an emotionally grounded outcome. This layered structure ensures that sentiment analysis is not confined to numeric polarity but is gauged as a communicative act mirroring cultural meaning.

The addition of a mathematical representation to the framework also sets it apart from previous descriptive frameworks. It allows for testing the relationships between linguistic, cultural, and emotional variables thereby, giving researchers the capability to measure interaction effects while still leaving room for interpretive insight. This combined ability opens up the framework for use in both qualitative and quantitative research.

In effect, the new framework boosts sentiment analysis beyond the boundaries set by algorithmic precision. It brings in a human, centred viewpoint which connects language, culture, and emotion within one analytical framework. This framework can be utilized to study intercultural communication, digital discourse, and marketing in a way that it helps to reveal the construction and reception of emotion across societies. Subsequent investigations may use this framework to examine the correlations between the use of certain linguistic strategies and emotional perception, thereby leading the discipline to a more thorough and inclusive understanding of sentiment.

ACKNOWLEDGEMENT

The authors would like to express gratitude to colleagues and reviewers who provided constructive feedback during the preparation of this paper. Special appreciation is extended to Universiti Teknologi MARA for continuous academic support.

https://doi.org/10.37134/kupasseni.vol14.sp.11.2026

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

AUTHORS' CONTRIBUTION

Sheema Liza Idris: Writing the initial original draft preparation, Preparation, creation and/or presentation of the published work, **Masurah Mohamad**: Writing, reviewing and Editing. Development of Data of Methodology.

AVAILABILITY OF DATA AND MATERIALS

Please choose one of the applicable statements below.
1. Data available within the article or its supplementary materials.

DECLARATION OF GENERATIVE AI

Authors must declare the use of generative AI in scientific writing upon submission of the paper. KUPAS SENI's AI author policy states that authors are allowed to use generative AI and AI-assisted technologies in the writing process before submission, but only to improve the language and readability of their paper and with the appropriate disclosure.

During the preparation of this work, the author(s) used CHATGPT to enhance the clarity of the writing. After using the CHATGPT, the author(s) reviewed and edited the content as needed and took(s) full responsibility for the content of the publication.

ETHIC STATEMENTS

Ethical approval statements will usually include: Not applicable.

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