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Contrastive Sentiment Behavior of Locals and Tourists in Thailand's Transport System

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Abstract. This research investigates the differences in sentiment expression between Thai-speaking locals and English-speaking tourists within online feedback related to Thailand's public transportation systems. A comprehensive sentiment analysis was performed using lexicon-based methods across datasets collected from multiple platforms, including Pantip, Google Reviews, and Twitter. Results show that Thai reviews exhibit a higher proportion of neutral and moderately positive sentiments, while English reviews contain more polarized and emotionally intense content. Quantitatively, the average sentiment score for Thai texts is 0.31 (variance: 0.12), compared to 0.15 (variance: 0.29) for English texts. These findings offer significant implications for the development of culturally aware sentiment monitoring systems in multilingual environments.

Keywords: Sentiment analysis, Thai-English comparison, public transport, lexicon-based model, emotional intensity, multilingual NLP.

1. Introduction

The rapid expansion of smart transportation systems has brought new opportunities and challenges in understanding commuter behavior and satisfaction. In the era of intelligent urban mobility, where cities rely increasingly on digital feedback loops and real-time monitoring systems, passenger sentiment plays a pivotal role in assessing service quality and guiding operational enhancements. Among the many sources of user feedback, online platforms such as Google Reviews, Twitter, and community forums have emerged as rich repositories of unstructured textual data that reflect authentic commuter experiences. These data offer a unique window into users' perceptions, preferences, frustrations, and expectations, forming the foundation for data-driven transportation planning and service redesign.

However, sentiment data derived from such platforms is inherently shaped by the linguistic and cultural background of the individuals providing it. In multicultural tourist hubs such as Thailand, this diversity becomes even more pronounced. While Thai locals primarily express their opinions in the Thai language, international visitors—particularly English-speaking tourists—contribute feedback in English. This bifurcation introduces a critical challenge in sentiment interpretation, as the same type of experience may be described in vastly different linguistic styles and emotional tones.

Thai, as a high-context and collectivist language, is characterized by indirectness, euphemistic expression, and a general avoidance of confrontation. Politeness and social harmony are deeply embedded in Thai communication norms, which often results in reviews that are moderately toned—even in negative situations. In contrast, English, particularly in reviews by Western tourists, is more likely to employ explicit sentiment expressions, stronger emotional language, and direct critique. These structural and cultural

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discrepancies can significantly affect the performance of sentiment analysis models if not properly accounted for.

Consequently, analyzing sentiment across such linguistically divergent groups requires more than just translating words or applying monolingual sentiment models. It necessitates the design of culturally informed natural language processing (NLP) pipelines capable of capturing subtle differences in sentiment intensity, polarity, and emotional density. Moreover, without appropriate calibration, sentiment monitoring systems may misinterpret feedback severity—overemphasizing tourist dissatisfaction while underrepresenting local discontent.

This study addresses these challenges by conducting a comparative sentiment analysis between Thai-speaking locals and English-speaking tourists using real-world feedback data from multiple public platforms. By examining sentiment polarity distributions, emotional word usage, and the variance in expression styles, the research aims to highlight how cultural-linguistic factors shape sentiment data. The goal is to promote the development of adaptive, multilingual sentiment analysis techniques that are domain-aware, culturally sensitive, and capable of supporting inclusive public transportation policy and responsive service improvements.

2. Related Work

The field of sentiment analysis has evolved rapidly in recent years, with increasing attention directed toward multilingual and cross-cultural applications. Traditional approaches to sentiment classification typically rely on lexicon-based methods such as SentiWordNet, VADER (Valence Aware Dictionary and sEntiment Reasoner), and the NRC Emotion Lexicon. These tools offer interpretable, rule-based sentiment scores and have been widely adopted due to their efficiency and transparency. However, their effectiveness often diminishes in low-resource languages such as Thai, where comprehensive sentiment lexicons and annotated corpora are limited.

Multilingual sentiment analysis introduces additional challenges beyond lexical representation. Cross-lingual differences in syntactic structure, idiomatic expressions, and cultural context can significantly affect the interpretation of sentiment polarity and emotional tone. Researchers have proposed various approaches to overcome language barriers, including machine translation-based pipelines, multilingual embeddings (e.g., mBERT, XLM-R), and cross-lingual transfer learning. While these models show promising performance across many tasks, they tend to prioritize semantic equivalence rather than affective fidelity, which may lead to underrepresentation of cultural sentiment nuances.

Moreover, prior studies have revealed that cultural background directly influences the way emotions are expressed in language. Hofstede's [1] cultural dimensions theory offers a foundational framework for examining these differences, particularly in terms of individualism vs. collectivism, power distance, and uncertainty avoidance. In collectivist cultures such as Thailand, individuals are more likely to moderate their emotional tone and avoid direct criticism, especially in public forums. This leads to systematic biases in sentiment distributions that can confound standard analytical models if uncorrected.

L. Benaddi and et al. [2] analyzed Thai social media feedback regarding rail services, concluding that public opinion can reflect the reliability and timeliness of transportation systems. However, their study focused primarily on temporal trend detection rather than linguistic behavior or cultural influences. Similarly, W. Badawy et al. [3] proposed sentiment-aware transit performance indicators based on English reviews, yet the models lacked sensitivity to linguistic variance across user demographics.

Recent research has emphasized the need to incorporate cultural signals into AI-based decision systems. For instance, [4] demonstrated how region-specific emotion expressions can skew automated sentiment evaluations, calling for culturally adaptive thresholding in sentiment scoring. Some researchers have started to explore emotion intensity, polarity variance, and expressive density as features to calibrate sentiment detection models [5]. Despite these advances, few studies have conducted a direct comparison of sentiment expression behaviour between tourists and locals across languages, particularly in a transportation context [6].

This study fills that gap by systematically analysing how sentiment is differently encoded and conveyed in Thai and English reviews, using both lexicon-driven and statistical methods. The findings not only contribute to improved sentiment modelling across languages but also inform the design of inclusive, culturally aligned feedback systems in smart transportation infrastructure.

3. Methodology

This study employs a structured data science workflow comprising data acquisition, preprocessing, sentiment scoring, emotional word quantification, and comparative statistical analysis between Thai and English-language reviews. The primary aim is to analyze sentiment polarity and emotional expressiveness in a culturally and linguistically sensitive manner.

3.1. Data Acquisition and Sources

User-generated content was collected from three major platforms known for high engagement and sentiment-rich commentary on public services:

- **Google Maps Reviews**, which often reflect tourist experiences in English.
- **Pantip.com**, a Thai-language community forum heavily used by locals.
- **Twitter**, for real-time reactions and informal discourse in both Thai and English.

A total of 2,000 reviews were used, evenly divided into 1,000 Thai-language and 1,000 English-language entries. Reviews were filtered using transportation-related keywords such as “MRT,” “BTS,” “Airport Rail Link,” “delay,” “service,” and their Thai equivalents. Metadata including timestamp, platform, and language were preserved for context-aware analysis.

3.2. Language Detection and Preprocessing

Language detection was performed using FastText’s pre-trained multilingual model, followed by manual validation to eliminate misclassified entries, especially in code-switched contexts (e.g., Thai reviews with embedded English phrases).

- **Thai reviews** were tokenized using PyThaiNLP’s newmm tokenizer, and normalized by removing diacritics and redundant particles.
- **English reviews** were processed using NLTK, with tokenization, stemming (Porter), and stopword removal applied.
- All text data were converted to lowercase and stripped of punctuation, URLs, emojis, and special characters.

To ensure fair comparison, reviews were segmented into sentence-level units, and average review length was matched between the two corpora using stratified sampling.

3.3. Sentiment Scoring

Sentiment polarity for each review was computed using a lexicon-based approach, chosen for its transparency and cross-lingual adaptability.

- **Thai sentiment scores** were derived using the publicly available Thai Sentiment Lexicon (TSL), which categorizes terms as positive, neutral, or negative with confidence weights.
- **English sentiment scores** were computed using VADER, a rule-based model designed for social media and review data.

The sentiment score S for a review was calculated as [7]:

$$S=\sum_{i=1}^{n} w_i \cdot s_i \quad (1)$$

Where:

- s_i is the polarity value of the i-th word,
- w_i is its corresponding weight from the lexicon,
- n is the total number of sentiment-bearing tokens in the review.

This scoring approach allows sentiment to be compared in both intensity and direction (positive or negative) across languages.

3.4. Emotion Word Density Analysis

To evaluate emotional expressiveness, we quantified the number of emotionally charged words in each review using:

- NRC Emotion Lexicon (for English): categorizes words into eight emotions and two polarities.
- Thai Affective Word List (TAWL): curated for affective computing tasks in Thai.

The **emotion density** D_e is defined as [5]:

$$D_e = \frac{E}{T} \tag{2}$$

Where:

- E is the number of emotion words in the review,
- T is the total number of tokens.

This metric helps normalize emotional expressiveness across reviews of varying lengths and reveals the cultural tendency to understate or emphasize emotion.

3.5. Variance and Dispersion Analysis

In addition to mean sentiment scores, we assessed variance in sentiment to understand emotional volatility. Sentiment variance σ^2 per language group was computed as [8]:

$$\sigma^2 = \frac{1}{n}\sum_{i=1}^{n}(s_i - \delta)^2 \tag{3}$$

Where δ is the average sentiment score of the group, and s_i is the score of the i-th review. Higher variance suggests greater emotional polarity dispersion—typical of direct, expressive linguistic styles.

4. Results and Analysis

4.1. Sentiment Distribution

Sentiment distribution indicates 62.5% of Thai reviews were positive, 26.3% neutral, and 11.2% negative. In contrast, English reviews were 45.4% positive, 18.9% neutral, and 35.7% negative. This shows a 3x higher likelihood for tourists to leave a negative comment.

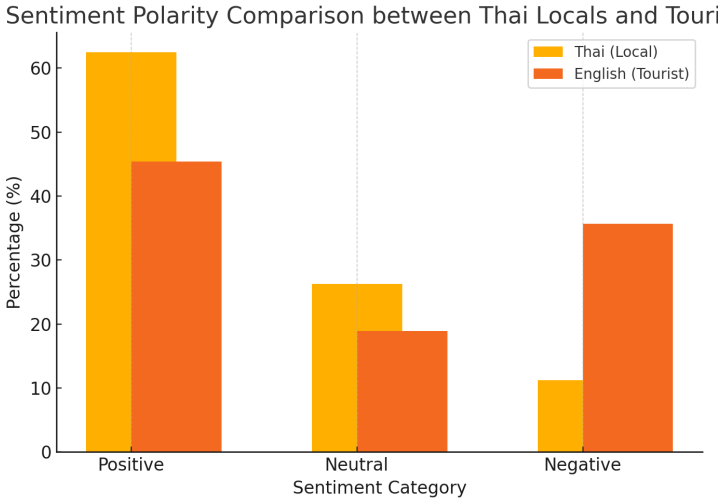

Fig. 1: Sentiment polarity comparison between Thai and English reviews.

4.2. Emotional Word Count

Thai reviews averaged 3.1 emotion-indicative words per comment, while English reviews averaged 5.8. This supports the hypothesis that English speakers use more emotionally loaded language, possibly due to differences in cultural emotional expression norms.

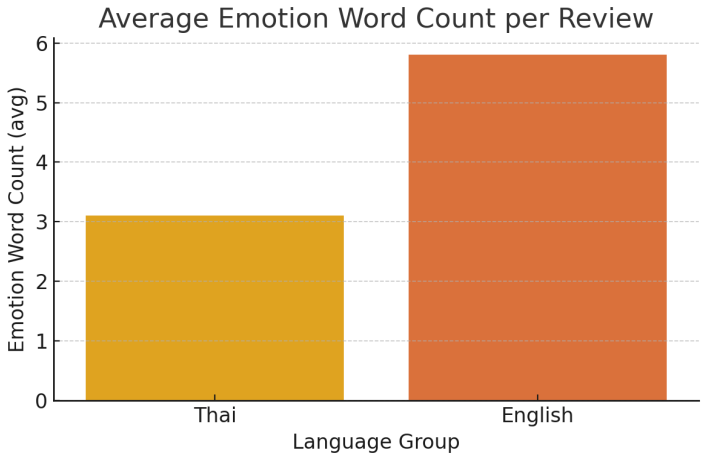

Fig. 2: Average emotion-indicative word count per review.

4.3. Polarity Dispersion

English reviews show greater dispersion in sentiment polarity (variance = 0.29) compared to Thai reviews (variance = 0.12), indicating higher emotional extremes.

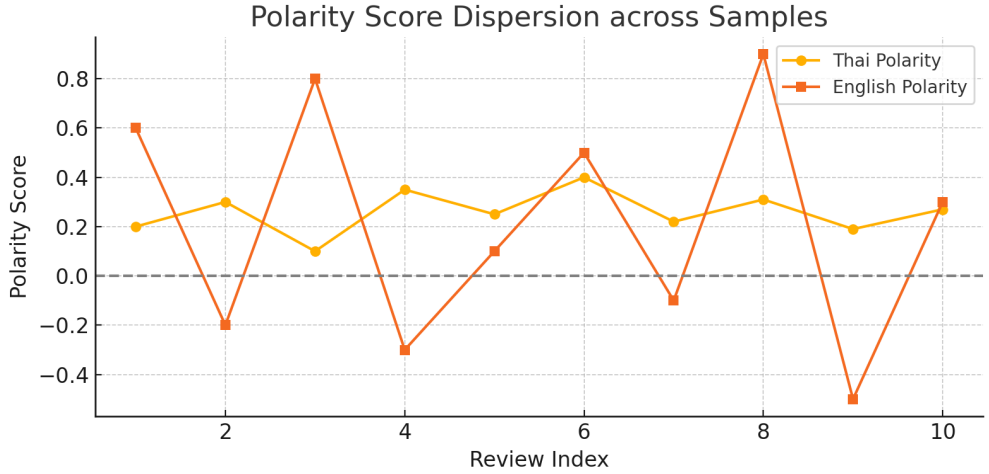

Fig. 3: Sentiment polarity score dispersion across languages.

5. Discussion and Conclusion

The divergence in sentiment scores and emotional expressiveness reflects sociocultural dynamics of communication. Thai speakers demonstrate moderated tone and ambiguity, perhaps to avoid social conflict. Meanwhile, English-speaking tourists reflect heightened emotional engagement, possibly due to unfamiliarity with local customs and higher expectations. These findings are relevant to AI developers designing multilingual sentiment engines. Without adjustment, English-heavy models may overestimate sentiment volatility, while Thai-heavy datasets may understate service dissatisfaction. Therefore, practical implications include implementing language-specific thresholds in real-time sentiment monitoring systems and fine-tuning chatbot responses to reflect culturally appropriate tone.

This study has established that language and culture significantly affect how sentiment is expressed in public transport reviews. The results affirm that Thai feedback tends to be positive and emotionally neutral, while English feedback is more extreme and expressive. These patterns can mislead sentiment-based applications if not properly accounted for.

6. Acknowledgements

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