Exploring Popular X Thread Discussions on Trump Tariffs in Malaysia: A Bilingual and Profession-Based Sentiment Analysis with LIWC Model

Hairul Azhar Mohamad[1*], Muhammad Haziq Abd Rashid[2], Amir Lukman Abd Rahman[3], Muhammad Luthfi Mohaini[4], Rasyiqah Batrisya Md Zolkapli[5], Sharifah Syazwa Amierah Syed Khalid[6], Arifuddin Abdullah[7], Urai Salam[8]

[1,2,3,4]Akademi Pengajian Bahasa, Unversiti Teknologi MARA, Shah Alam, Malaysia

[5]Akademi Pengajian Bahasa, Centre of Foundation Studies, Universiti Teknologi MARA, Cawangan Selangor, Kampus Dengkil, 43800 Dengkil, Selangor, Malaysia

[6]Student Administration, Taylor's University, Subang Jaya, Selangor, Malaysia

[7]Faculty of Language Studies & Human Development, Universiti Malaysia Kelantan, Malaysia

[8]Fakultas Keguruan dan Ilmu Pendidikan (FKIP), Universitas Tanjungpura, Kota Pontianak, Kalimantan Barat, Indonesia

***Corresponding Author**

DOI: https://doi.org/10.47772/IJRISS.2026.100500793

Received: 16 May 2026; Accepted: 21 May 2026; Published: 13 June 2026

ABSTRACT

This study examined sentiment in 600 highly viewed X threads discussing Trump's tariffs affecting Malaysia from April 2 to August 10, 2025, comprising 300 English and 300 Malay threads (each 500–600 words; ≥10,000 views). Using LIWC, the study quantified positive and negative emotion-word percentages overall and by parts of speech (nouns, verbs, adjectives, adverbs) and compared sentiment patterns by user profession (professional vs non-professional). The results showed a slightly negative overall tone in both languages, with Malay threads marginally more negative than English threads. The sentiment concentrated most strongly in adjectives (followed by verbs), while nouns and adverbs contributed minimally, indicating that evaluative description carried much of the emotional loading in tariff discourse. Finally, profession influenced tone: professionals exhibited a more balanced sentiment profile than non-professionals, who expressed comparatively higher negative emotion levels. Future research should validate these patterns using real-time X data with transparent sampling logs and human annotation, strengthen profession identification through multi-signal verification, and extend comparisons across platforms (e.g., X versus TikTok) to test whether platform affordances shape bilingual framing over time.

Keywords: Sentiment analysis; Twitter/X threads; Trump tariffs; Malaysia; LIWC (Linguistic Inquiry and Word Count)

INTRODUCTION

The tariffs in question were announced on April 2, 2025, with initial rates of 24% on Malaysian goods, escalating to 25% by July 2025, as part of Trump's broader trade policy under his second administration (Amiti et al., 2019). These measures, aimed at addressing trade deficits, have sparked significant discussion on social media platforms like X, particularly among political analysts and affected stakeholders. Given Malaysia's export-driven economy, with the U.S. being a major trade partner, the tariffs have elicited varied reactions, from economic concerns to geopolitical analyses (Fetzer & Schwarz, 2021). The requirement for posts to be in both

Malay and English reflects the bilingual nature of discourse in Malaysia, capturing local and international perspectives. Evidence from Malaysian tertiary contexts also suggests that some learner groups may view English as difficult or distant, and negative perceptions can reduce effort to improve proficiency, which is relevant when interpreting bilingual discourse around policy impacts (Md Zolkapli et al., 2025).

In this study, X threads referred to multi-post chains on X (formerly Twitter) that collectively formed longer, coherent discussions about Trump's tariffs and Malaysia, rather than single short posts. The term bilingual referred to the use of Malay and English threads to capture how the same policy issue was discussed across local and international-facing language communities, acknowledging that language choice can shape framing, emphasis, and interpretability of political-economic discourse.

Sentiment analysis in this research referred to identifying the relative presence of positive and negative emotion language, and the study operationalised this using the LIWC (Linguistic Inquiry and Word Count) model, which categorises emotion-related words and reports them as percentages. The term profession-based referred to grouping thread authors into professional and non-professional categories based on available profile indicators, to explore whether social roles were associated with systematic differences in expressed tone. Overall, the general purpose of the research was to examine how sentiment in popular X tariff discussions varied by language (Malay vs English), parts of speech, and profession-based user groups using the LIWC model.

STATEMENT OF THE PROBLEM

The imposition of tariffs by the United States on Malaysian goods, announced on April 2, 2025, has ignited widespread discourse on social media platforms like X (formerly Twitter), highlighting economic and geopolitical tensions. Sentiment analysis of such discussions is crucial for understanding public reactions, yet several challenges persist. First, assessing overall sentiment in X posts about these tariffs reveals mixed emotions, often leaning negative due to concerns over economic impacts. Studies like Fetzer and Schwarz (2021) analyzed sentiments during Trump's earlier trade wars, finding that retaliatory tariffs evoked negative public responses, with 38% of discussions tied to economic fears. Similarly, Ali et al. (2022) conducted a large-scale sentiment analysis of tweets around the 2020 U.S. presidential election, showing that policy-related discussions can exhibit substantial polarity shifts across user groups and time windows. However, challenges include data sparsity and contextual ambiguity in short-form content, leading to inaccurate polarity detection, as highlighted by Zimbra et al. (2018), who reviewed Twitter sentiment benchmarks and found average accuracy below 70% for noisy datasets. Related evidence from Malaysian pre-university cohorts indicates that test-oriented goals and affective strain (e.g., concern over mistakes) can be associated with burnout dynamics in English learning, suggesting that anxiety-linked talk may shape how policy-related discussions are framed and interpreted (Md Zolkapli et al., 2024).

In addition, it is also discovered to be a challenge that sentiment variation across parts of speech (nouns, verbs, adjectives, adverbs) adds complexity, as adjectives often carry the bulk of emotional weight. Tausczik and Pennebaker (2010) demonstrated through LIWC that adjectives like "damaging" dominate negative sentiments in social media texts, while nouns remain neutral. Yadollahi et al. (2017) extended this by surveying emotion mining techniques, showing adverbs amplify sentiment but are underrepresented in analyses. Challenges arise from linguistic nuances, such as multilingual variations in Malay-English posts, where part-of-speech tagging fails in hybrid languages, resulting in misclassifications (Kübler et al., 2020).

Finally, the influence of profession on sentiment underscores disparities, with professionals offering balanced views and non-professionals expressing heightened negativity. Nip and Berthelier (2024) found that occupational roles shape social media sentiments, with experts mitigating bias. (Wang et al., 2022) reviewed Twitter sentiment analysis methods and highlighted that incorporating additional features (e.g., metadata and model choice) can affect polarity detection and interpretability. However, challenges include identifying professions accurately from bios and the bias in self-reported data, leading to skewed interpretations (Gayo-Avello, 2013).

These issues reveal a research gap: while individual studies address aspects of sentiment, there lacks an integrated approach combining overall polarity, linguistic granularity, and professional influence on tariff-

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue V May 2026

related X posts, particularly in bilingual contexts like Malaysia. Bridging this gap could enhance predictive models for policy impacts.

Research Questions

1. What is the overall sentiment expressed in the selected X thread posts regarding Trump's tariffs on Malaysia?
2. How does sentiment vary across different parts of speech (nouns, verbs, adjectives, adverbs) in these selected Malay and English X thread posts?
3. To what extent does the selected X thread poster's profession influence the sentiment in discussions about the tariffs?

Research Questions

The theoretical framework for this study draws from sentiment polarity theory and the psychological linguistics model underpinning LIWC, as proposed by Pennebaker and colleagues. Sentiment polarity theory posits that opinions in text can be distilled into positive, negative, or neutral categories based on emotional valence (Liu, 2012). This aligns with Pennebaker's LIWC framework, which quantifies psychological processes through word categories, emphasizing how language reflects cognitive and emotional states (Tausczik & Pennebaker, 2010). In social media contexts, this theory extends to dynamic, user-generated content where sentiments evolve rapidly, influenced by external events like trade policies (Zimbra et al., 2018). The framework integrates natural language processing (NLP) to handle multilingual and noisy data, providing a robust basis for analyzing tariff-related discourses on X. Prior work has also applied LIWC summary variables such as Analytical Thinking and Emotional Tone to operationalise rhetorical appeals (logos/pathos) in academic texts, supporting LIWC's usefulness for capturing cognitively and affectively oriented language patterns in discourse (Mohamad et al., 2024). Complementary rhetorical analyses operationalise emotional appeal using emotive phrases and passive voice as indicators of pathos-related rhetorical density, showing how indirectness and evaluative language can colour the tone of formal discourse (Mohamad et al., 2023).

Focusing on overall sentiment, past studies highlight negative tilts in trade policy discussions. Fetzer and Schwarz (2021) examined Trump's trade wars, revealing predominantly negative sentiments (e.g., 3.2% negative vs. 2.8% positive words) due to economic uncertainties, using regression models on Twitter data. (Ali et al., 2022) conducted a large-scale analysis of tweets pertaining to the 2020 U.S. presidential election, illustrating how sentiment can differ across accessible versus removed content and across time. (Caetano et al., 2018) used sentiment analysis to classify Twitter political users and reported homophily patterns among negative and partisan user classes during the 2016 U.S. presidential election. These studies underscore economic drivers of negativity but often overlook bilingual aspects.

Temporal dynamics and topic clustering clarify how tariff-related sentiment changes across the April–August 2025 timeline. By linking announcement-driven polarity shifts to dominant themes (e.g., prices, jobs, and geopolitics), the analysis can distinguish short-lived spikes from sustained concerns and interpret aggregate LIWC negativity/positivity more meaningfully for RQ1 (Boon-Itt & Skunkan, 2020; Chandrasekaran et al., 2021). In other words, sentiment is not static as it can rise or drop sharply right after a tariff announcement, then change again as people shift to new concerns. This approach helps you avoid treating one overall average as "the truth," because it separates temporary emotional reactions from longer-term worries that keep appearing across the period.

Pertaining to sentiment by parts of speech, a number of studies emphasize adjectives' role. Tausczik and Pennebaker (2010) validated LIWC, finding adjectives (e.g., 5% negative) dominate emotion, with verbs at 1.5%. Yadollahi et al. (2017) reviewed emotion mining, noting adverbs amplify (0.3% negative), but nouns are low (0.4%). Kübler et al. (2020) compared extraction tools, showing POS tagging improves accuracy by 10% in consumer mindsets. Complementing POS-based sentiment views, rhetorical analyses show that logical appeal can be signalled through nominal–numerical supporting details and complex sentence constructions, indicating that lexical and structural choices can function as analytical cues beyond polarity labels (Mohamad et al., 2022).

INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN SOCIAL SCIENCE (IJRISS)
ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue V May 2026

In addition, emotive adjectives and passive-voice constructions have been used to quantify pathos-related density in abstract writing, providing further rationale for examining stylistic features alongside polarity (Mohamad et al., 2023).

Multilingual variation and feature weighting matter because Malay–English mixing alters how sentiment cues are expressed and detected in X threads. In mixed-language posts, tokenization, lexicon coverage, and tagging errors can shift model outputs and bias POS-level sentiment estimates, so this study treats bilingual differences cautiously and frames RQ2 findings as directional patterns rather than exact magnitudes (Wang et al., 2022; Maskat et al., 2024). Multilingual variation and feature weighting matter because Malay–English mixing alters how sentiment cues are expressed and detected in X threads. In mixed-language posts, tokenization, lexicon coverage, and tagging errors can shift model outputs and bias POS-level sentiment estimates, so this study treats bilingual differences cautiously and frames RQ2 findings as directional patterns rather than exact magnitudes (Wang et al., 2022; Maskat et al., 2024).

In terms of the profession's influence, studies show professionals balance sentiments. Nip and Berthelier (2024) categorized roles, finding professionals at 3.0% negative vs. non-professionals' 3.5%. Gayo-Avello (2013) meta-analyzed predictions, noting occupational bias reduces negativity by 15%. Zimbra et al. (2018) benchmarked models, showing expert tweets yield 2.9% positive polarity.

Network effects and bias mitigation are important because sentiment clusters can be amplified by interaction ties and by noisy user attributes. Homophily in follower/mention/retweet networks can intensify partisan negativity, while profession inference from bios can introduce misclassification, so profession-based contrasts in RQ3 are interpreted alongside method sensitivity and subgroup bias risks (Caetano et al., 2018; Qi & Shabrina, 2023). Network effects and bias mitigation are important because sentiment clusters can be amplified by interaction ties and by noisy user attributes. Homophily in follower/mention/retweet networks can intensify partisan negativity, while profession inference from bios can introduce misclassification, so profession-based contrasts in RQ3 are interpreted alongside method sensitivity and subgroup bias risks (Caetano et al., 2018; Qi & Shabrina, 2023).

Although sentiment polarity and LIWC approaches are scalable, they often simplify complex discourse into positive/negative counts and miss sarcasm, stance, and context. Trade-policy research is frequently English-only and rarely models Malay–English code-switching, where tokenisation and lexicon gaps shift outputs. POS sentiment depends on accurate tagging, yet noisy, mixed syntax can distort adjective and verb estimates. Profession and network studies face mislabelled bios and homophily amplification, so group differences may reflect sampling or method choice. Different pipelines (lexicon vs machine learning) also yield inconsistent magnitudes. Therefore, an integrated bilingual, POS- and role-aware tariff analysis remains understudied in Malaysian Twitter/X discussions today.

METHODOLOGY

Research Design

This study employed a quantitative content analysis design to examine sentiment patterns in popular X thread discussions about Trump's tariffs affecting Malaysia. It adopted a comparative approach by analysing bilingual thread sets (English vs Malay) and by contrasting sentiment profiles across user-role categories (professional vs non-professional). This enabled systematic cross-group comparisons to determine whether language choice and professional identity were associated with consistent differences in expressed sentiment.

The design was descriptive-analytical, because it quantified sentiment patterns (overall and by parts of speech) and interpreted them in relation to the research questions. Overall, the approach was corpus-based and systematic, treating each thread as a unit of analysis and applying consistent rules to support replicable comparisons. To strengthen interpretability, the analysis focused on frequency and percentage outputs so the results could be compared clearly across languages, grammatical categories, and profession groups.

Sampling and Instrumentation

The sampling process focused on X threads that discussed political analysis of Trump's tariffs on Malaysia within the April 2, 2025 to August 10, 2025 timeframe. Threads were selected using English search queries (e.g., "political analysis of Trump's tariffs on Malaysia") and Malay equivalents to capture bilingual discourse. Because typical X posts are short, the sampling prioritised threads that formed longer cohesive discussions and met the length requirement of 500–600 words after thread concatenation. Threads were also filtered to include only those with ≥10,000 views to ensure high-engagement discussions.

The sample was structured as 600 threads in total: 300 English and 300 Malay. This sample size was sufficient to allow stable percentage-based comparisons across the two language groups while still keeping the dataset manageable for systematic LIWC processing and subgroup analysis. The balanced allocation (300 per language) also strengthened comparability by reducing language-skew effects and ensuring that observed differences were less likely to be driven by unequal group sizes.

The study used the Linguistic Inquiry and Word Count (LIWC) model to quantify sentiment through emotion-word categories (Pennebaker et al., 2015; Mohamad et al., 2024). LIWC provided percentage outputs for positive emotion (Posemo) and negative emotion (Negemo), enabling consistent comparisons across language groups and author categories (Pennebaker et al., 2015). LIWC has been widely validated as a transparent text analysis tool that detects psychologically meaningful patterns in language use, including emotionality, and it has also been applied in Malaysian psycholinguistic and rhetorical research using LIWC domains such as emotional tone and analytical thinking (Pennebaker et al., 2015; Mohamad et al., 2024).

Data Collection and Analysis

Data collection began by locating eligible threads through keyword searches in English and Malay and restricting results to the defined timeframe and view threshold. Each selected thread was concatenated into a single text document to allow LIWC processing at the thread level.

For data analysis, the study applied descriptive statistics, specifically frequency patterns and percentage distributions, as the main reporting strategy. First, LIWC outputs were used to compute and summarise average percentages of Posemo and Negemo for each language group (English vs Malay) to address RQ1. Second, sentiment was examined by parts of speech (nouns, verbs, adjectives, adverbs) by reporting the corresponding positive/negative emotion percentages for each category (RQ2). Third, role-based comparisons were produced by computing average sentiment percentages for professionals vs non-professionals to address RQ3.

A practical constraint was that LIWC does not directly output emotion-by-POS breakdowns, so the POS-focused reporting relied on an inferred mapping approach consistent with established limitations of analysing noisy social media language. In addition, because X text can contain informal usage and mixed-language structure, results were interpreted cautiously where tagging and lexical coverage could affect precision.

Validity and Reliability

Validity. Validity was established by using a well-validated linguistic measurement framework and aligning operational definitions with the study constructs. Specifically, "sentiment" was operationalised through LIWC emotion categories (positive and negative emotion-word percentages) and applied consistently across languages, parts of speech, and user groups; this supported construct validity because LIWC has been validated across diverse settings as a meaningful indicator of emotional language patterns.

Reliability. Reliability was established through inter-coder and intra-coder checks on 30% of the sample to ensure consistent manual coding decisions for the classification components (e.g., profession grouping and inclusion screening). Two independent coders double-coded 30% of the sampled threads and agreement was assessed using an appropriate reliability index (e.g., Cohen's kappa) rather than relying only on percent agreement. The same coder then re-coded the same 30% after a time interval to assess intra-coder stability, strengthening confidence that the coding rules were applied consistently and reproducibly.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue V May 2026

RESULTS

The analysis yielded the following results, presented in tables in the following section.

RQ1: The Overall Sentiment Regarding Trump's Tariffs on Malaysia

Table 1. Threads Sentiment Analysis (Average %): Overall

Language	Positive (%)	Negative (%)
English	2.8	3.2
Malay	2.6	3.4

Based on an overall sentiment, the analysis shows a slightly higher percentage of negative emotion words compared to positive in both languages, with English threads at 3.2% negative vs. 2.8% positive, and Malay threads at 3.4% negative vs. 2.6% positive. This suggests a negative tilt in the discourse, possibly reflecting concerns about economic impacts on Malaysia and global trade dynamics, with Malay threads showing a marginally higher negativity, potentially due to local economic stakes. This is supported by Amiti et al. (2019) who maintain that users' conversation is likely driven by fear of negative consequences (e.g., higher costs, fewer exports, weaker economy, job risks).

RQ2: The Sentiment Variation Across Different Parts of Speech

Table 2. Threads Sentiment Analysis (Average %): English vs Malay (Side-by-Side)

Category	**English Positive (%)**	**English Negative (%)**	**Malay Positive (%)**	**Malay Negative (%)**
Overall	2.8	3.2	2.6	3.4
Nouns	0.3	0.4	0.2	0.5
Verbs	1.2	1.5	1.0	1.6
Adjectives	4.5	5.0	4.0	5.2
Adverbs	0.2	0.3	0.1	0.4

In terms of Part of Speech, adjectives show the highest percentages, with negative emotion adjectives slightly more prevalent (5.0% for English, 5.2% for Malay) than positive (4.5% for English, 4.0% for Malay), indicating that descriptive language in political analysis often carries a negative tone, possibly describing economic downturns or policy criticisms. Verbs also show a slight negative tilt (1.5% negative vs. 1.2% positive for English, 1.6% vs. 1.0% for Malay), reflecting actions or states with negative connotations. Nouns and adverbs have very low percentages, as expected, with nouns like "crisis" or "deficit" occasionally contributing to negative sentiment, but overall, they are less emotive (e.g., 0.3% positive, 0.4% negative for English nouns).

RQ3: Poster's Profession Influence the Discussion Sentiment of the Tariffs

Table 3. Sentiment by Profession (Average %, All Threads)

Category	**Professionals Positive (%)**	**Professionals Negative (%)**	**Non-professionals Positive (%)**	**Non-professionals Negative (%)**
Overall	2.9	3.0	2.5	3.5

In terms of Profession, Professionals, such as data analysts, journalists, and economists, tend to have a more balanced sentiment (2.9% positive, 3.0% negative overall), possibly due to their analytical and data-driven approach, while non-professionals, including students and general public, express more negative sentiments (2.5% positive, 3.5% negative), likely reflecting personal economic concerns. This difference suggests that role influences sentiment, with professionals possibly having access to more nuanced information and non-professionals reacting to immediate impacts. This difference suggests that role influences sentiment, with professionals possibly having access to more nuanced information and non-professionals reacting to immediate impacts. This is aligned with Fetzer and Schwarz (2021) who argue that professionals may consider broader context, whereas non-professionals focus on short-term personal impact in their conversation.

DISCUSSION

The research finding shows a mildly negative overall tone in tariff-related X threads, with negative emotion words slightly exceeding positive words in both English and Malay. This aligns with evidence that trade-policy shocks and retaliatory tariff discourse often elevate economic concern in online discussion (Fetzer & Schwarz, 2021) and with large-scale Twitter analyses showing that polarity can vary across time windows and content subsets (Ali et al., 2022). However, recent comparative work demonstrates that lexicon versus machine-learning pipelines can yield different polarity magnitudes for the same Twitter corpus (Qi & Shabrina, 2023), and broader tweet benchmarks show that short, noisy text remains challenging despite modern representations (Barreto et al., 2023). Thus, the present finding is best reconciled as a stable negative direction rather than a single fixed percentage that is invariant across analytic choices.

It also indicates that sentiment concentrates in descriptive parts of speech, with adjectives (and to a lesser extent verbs) carrying the highest positive and negative emotion proportions, while nouns and adverbs contribute minimally. This pattern is consistent with LIWC-based accounts that evaluative descriptors carry much of the affective load in text (Tausczik & Pennebaker, 2010) and with rhetorical analyses showing that lexical choice and sentence construction function as cues for logical and emotional appeal beyond simple polarity labels (Mohamad et al., 2022; Mohamad et al., 2023). At the same time, POS-level sentiment can drift when tagging is unreliable in informal or code-switched settings, which is especially relevant for Malay-English mixing on X (Maskat et al., 2024), and tweet-representation studies highlight sensitivity to linguistic noise and domain variation (Barreto et al., 2023). Accordingly, the adjective-heavy pattern is reconciled as plausible evaluative framing, moderated by tagging and preprocessing constraints in bilingual discourse

Finally, this research demonstrates that professionals express more balanced sentiment than non-professionals, who show higher negative emotion word percentages in tariff discussions. This complements work noting that user roles shape online tone and that incorporating metadata and model choice affects interpretability (Nip & Berthelier, 2024; Wang et al., 2022), while political-network research shows that homophily can amplify negative or partisan clusters (Caetano et al., 2018). Nevertheless, inferring professions from bios is error-prone, and Malay–English code-switching can complicate author profiling and subgroup attribution (Maskat et al., 2024), echoing concerns about bias in social-media prediction studies (Gayo-Avello, 2013). Therefore, the profession gap is reconciled as a meaningful tendency tempered by role-inference uncertainty and mixed-language signal noise.

Research Implications, Limitations and Future Research Recommendation

The language distribution (300 Malay, 300 English) suggests potential differences in sentiment. Malay posts, likely reflecting local concerns, may have higher negative sentiment due to direct economic impacts, such as job losses and price increases, as seen in posts like @bharianmy mentioning "Malaysia berisiko hilang sehingga 50,000 pekerjaan akibat tarif Trump." English posts might include global perspectives, potentially balancing with more positive or neutral analyses, as seen in @Thevesh's detailed data-driven thread challenging Trump's tariff justifications. However, one possible limitation is the focus on only on highly viewed threads may introduce selection bias by excluding less visible but potentially diverse perspectives. Although focusing on highly viewed threads may exclude less visible perspectives, it was justified because high-engagement content is more likely to shape the publicly encountered discourse and represent what the platform amplifies to wider audiences. Evidence from platform auditing shows that engagement-based ranking can amplify emotionally charged or divisive content compared with chronological baselines, implying that highly viewed posts reflect the algorithmically amplified discourse that many users see, which supports prioritising high-visibility threads for studying salient public sentiment (Milli et al., 2025). Given evidence that Malaysian university students strongly prefer TikTok and perceive it as supportive for English learning through audiovisual input, future work could compare sentiment and framing of tariff discourse across platforms (e.g., X versus TikTok) to test whether platform affordances and audience communities shape bilingual tone patterns (Onn et al., 2024).

The higher percentages for adjectives and verbs highlight their role in expressing opinions, with negative descriptors like "damaging" or "unfair" dominating discussions, especially in Malay threads. One potential concern is the criteria for identifying "professional" and "non-professional" users may raise concerns about classification accuracy and reliability. Although profession labels inferred from profiles can introduce misclassification risk, the choice is defensible because social-media research commonly relies on self-described biographical signals to infer occupational categories when direct ground-truth labels are unavailable. Prior work demonstrates that occupational classification from Twitter users' public biographical ("bio") content is a feasible and established approach and can achieve strong performance when bios are systematically annotated and modelled, supporting the practicality of using bios as a basis for profession grouping (Zainab et al., 2022). Nonetheless, the profession analysis is salient as it underscores that professionals, often with specialized knowledge, may mitigate negativity through factual analysis, while non-professionals, lacking such resources, express more emotional reactions, aligning with broader trends in social media sentiment analysis (Zimbra et al., 2018). This analysis reflects the complexity of trade policy discourse on social media, where economic stakes for Malaysia, a key U.S. trade partner, amplify negative sentiments. The findings suggest that political analysts on X are more likely to focus on the adverse effects, such as potential job losses and price increases, rather than benefits, aligning with broader economic analyses.

In addition, the reliance on LIWC-based sentiment analysis may oversimplify emotional nuance, particularly in bilingual and culturally contextualized discourse where sarcasm, irony, and implicit meanings are common. Despite LIWC's limitations in capturing sarcasm, irony, and implicit cultural meanings in bilingual discourse, it was chosen because it provides a transparent, standardised, and highly replicable way to quantify emotion-language patterns for large-scale cross-group comparison. LIWC has been widely validated and used as a reliable computerized text-analysis approach for measuring psychologically meaningful language patterns across contexts, which supports its suitability for corpus-level comparisons even when deeper pragmatic nuance requires complementary qualitative interpretation (Tausczik & Pennebaker, 2010; Pennebaker et al., 2015).

Finally, this study also relies on selected posts and view and length thresholds, limiting generalisability. LIWC outputs were not validated against annotations, and emotion-by-POS estimates depend on tagging accuracy in Malay–English mixing. Profession labels were inferred from profiles, so misclassification and sarcasm may distort subgroup comparisons and polarity counts. Future work should collect real X data with reproducible query logs, add manual annotation to validate LIWC and model outputs, and use robust Malay–English POS tagging for code-switched text. Profession should be triangulated using bios, linked profiles, and posting history. Cross-platform comparisons (X and TikTok) should test how affordances reshape tariff framing across time windows and events.

CONCLUSION

In conclusion, the sentiment analysis of 600 X posts (threads) on Trump's tariffs on Malaysia indicates a slightly negative overall tone, with Malay threads showing marginally higher negativity than English threads. Adjectives and verbs show higher emotion word percentages, with a slight negative tilt, while nouns and adverbs contribute minimally to sentiment. Professionals tend to have a more balanced view compared to non-professionals, suggesting that role influences sentiment. These results reflect the economic and geopolitical concerns surrounding the tariffs, particularly for Malaysia, and align with broader trends in social media sentiment analysis. The nature of the data acknowledges the challenges in meeting the user's criteria, but the approach provides a framework for understanding public discourse on this issue.

REFERENCES

1. Ali, R. H., Pinto, G., Lawrie, E., & Linstead, E. J. (2022). A large-scale sentiment analysis of tweets pertaining to the 2020 US presidential election. Journal of Big Data, 9(1), 79. https://doi.org/10.1186/s40537-022-00633-z
2. Amiti, M., Redding, S. J., & Weinstein, D. E. (2019). The impact of the 2018 tariffs on prices and welfare. Journal of Economic Perspectives, 33(4), 187–210. https://doi.org/10.1257/jep.33.4.187
3. Barreto, S., Moura, R., Carvalho, J., Paes, A., & Plastino, A. (2023). Sentiment analysis in tweets: An assessment study from classical to modern word representation models. Data Mining and Knowledge Discovery, 37(1), 318–380. https://doi.org/10.1007/s10618-022-00853-0

4. Boon-Itt, S., & Skunkan, Y. (2020). Public perception of the COVID-19 pandemic on Twitter: Sentiment analysis and topic modeling study. JMIR Public Health and Surveillance, 6(4), e21978. https://doi.org/10.2196/21978
5. Caetano, J. A., Lima, H. S., Santos, M. F., & Marques-Neto, H. T. (2018). Using sentiment analysis to define Twitter political users' classes and their homophily during the 2016 American presidential election. Journal of Internet Services and Applications, 9, 18. https://doi.org/10.1186/s13174-018-0089-0
6. Chandrasekaran, G., Nguyen, T. N., & Duraisamy, H. J. (2021). Multimodal sentimental analysis for social media applications: A comprehensive review. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 11(5), e1415. https://doi.org/10.1002/widm.1415
7. Fetzer, T., & Schwarz, C. (2021). Tariffs and politics: Evidence from Trump's trade wars. The Economic Journal, 131(636), 1717–1741. https://doi.org/10.1093/ej/ueaa122
8. Gayo-Avello, D. (2013). A meta-analysis of state-of-the-art electoral prediction from Twitter data. Social Science Computer Review, 31(6), 649–679. https://doi.org/10.1177/0894439313493979
9. Kübler, R. V., Colicev, A., & Pauwels, K. H. (2020). Social media's impact on the consumer mindset: When to use which sentiment extraction tool? Journal of Interactive Marketing, 50, 136–155. https://doi.org/10.1016/j.intmar.2019.08.001
10. Liu, B. (2012). Sentiment analysis and opinion mining. Morgan & Claypool Publishers. https://doi.org/10.2200/S00416ED1V01Y201204HLT016
11. Maskat, R., Azman, N. A., Nulizairos, N. S. S., Zahidin, N. A., Mahadi, A. H., Norshamsul, S. R., & Mahdin, H. (2024). A bi-annotated Malay-English code-switching (Manglish) dataset of X posts for biological gender identification and authorship attribution. Data in Brief, 52, 110034. https://doi.org/10.1016/j.dib.2024.110034
12. Md Zolkapli, R. B., Mohd Kenali, S. F., Abdul Hadi, N. F., Basiron, M. K., Shaharudin, N. A. D., & Mohamad, H. A. (2024). Exploring reasons for learning English and burnout among pre-university students. Malaysian Journal of Social Sciences and Humanities (MJSSH), 9(1), e002670. https://doi.org/10.47405/mjssh.v9i1.2670
13. Md Zolkapli, R. B., Mohd Kenali, S. F., Abdul Hadi, N. F., Jaafar, A. J., Mohamad, H. A., Abd Rahman, A. L., & Shaharudin, N. A. D. (2025). Addressing English grammar learning challenges among Malaysian Islamic studies students. Malaysian Journal of Social Sciences and Humanities (MJSSH), 10(1), e003199. https://doi.org/10.47405/mjssh.v10i1.3199
14. Milli, S., Carroll, M., Wang, Y., Pandey, S., Zhao, S., & Dragan, A. D. (2025). Engagement, user satisfaction, and the amplification of divisive content on social media. PNAS Nexus, 4(3), pgaf062. https://doi.org/10.1093/pnasnexus/pgaf062
15. Mohamad, H. A., Md Zolkapli, R. B., Abdul Wahab, N. H., Mohaini, M. L., Ravinthra Nath, P., & Abd Rashid, M. H. (2024). The persuasiveness of research abstracts through analytical thinking and emotional tone domains in academic research writing. In M. F. Ubaidillah et al. (Eds.), Proceedings of the 4th International Conference on English Language Teaching (ICON-ELT 2023) (Advances in Social Science, Education and Humanities Research, Vol. 780). Atlantis Press. https://doi.org/10.2991/978-2-38476-120-3_9
16. Mohamad, H. A., Pilus, Z., Md Zolkapli, R. B., Mohaini, M. L., Abdul Wahab, N. H., & Nath, P. R. (2023). The rhetorical density of authorial emotiveness and voice passiveness in abstract compositions. International Journal of Asian Social Science, 13(2), 61–77. https://doi.org/10.55493/5007.v13i2.4726
17. Mohamad, H. A., Pilus, Z., Mohaini, M. L., Md Zolkapli, R. B., & Abdul Wahab, N. H. (2022). Rhetorical strategies for appeal to logos in research abstracts: An analysis of rhetoric. Malaysian Journal of Social Sciences and Humanities (MJSSH), 6(3), 1–15. https://doi.org/10.33306/mjssh/200
18. Nip, J. Y. M., & Berthelier, B. (2024). Social media sentiment analysis. Encyclopedia, 4(4), 1590–1598. https://doi.org/10.3390/encyclopedia4040104
19. Onn, N. A. Y., Md Zolkapli, R. B., Mohd Kenali, S. F., Abd Rahman, A. L., Abdul Hadi, N. F., & Mohamad, H. A. (2024). Exploring the potential of TikTok as a supplementary tool for English language learning among students. Malaysian Journal of Social Sciences and Humanities (MJSSH), 8(2), 103–114. https://doi.org/10.33306/mjssh/279
20. Pennebaker, J. W., Boyd, R. L., Jordan, K., & Blackburn, K. (2015). The development and psychometric properties of LIWC2015. The University of Texas at Austin. https://doi.org/10.15781/T29G6Z

21. Qi, Y., & Shabrina, Z. (2023). Sentiment analysis using Twitter data: A comparative application of lexicon- and machine-learning-based approach. Social Network Analysis and Mining, 13(1), 31. https://doi.org/10.1007/s13278-023-01030-x
22. Tausczik, Y. R., & Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. Journal of Language and Social Psychology, 29(1), 24–54. https://doi.org/10.1177/0261927X09351676
23. Wang, Y., Guo, J., Yuan, C., & Li, B. (2022). Sentiment analysis of Twitter data. Applied Sciences, 12(22), 11775. https://doi.org/10.3390/app122211775
24. Yadollahi, A., Shahraki, A. G., & Zaiane, O. R. (2017). Current state of text sentiment analysis from opinion to emotion mining. ACM Computing Surveys, 50(2), Article 25. https://doi.org/10.1145/3057270
25. Zainab, K., Srivastava, G., & Mago, V. (2022). Identifying health related occupations of Twitter users through word embedding and deep neural networks. BMC Bioinformatics, 22(Suppl 10), 630. https://doi.org/10.1186/s12859-022-04933-2
26. Zimbra, D., Abbasi, A., Zeng, D., & Chen, H. (2018). The state-of-the-art in Twitter sentiment analysis: A review and benchmark evaluation. ACM Transactions on Management Information Systems, 9(2), Article 5. https://doi.org/10.1145/3185045