Supplementary Materials for "Tug-of-War of Emotion: Measuring and Modeling Sentiment Cycles in Chinese-language Pop Song Lyrics, 1967-2023"

1. Lyric sentiment cycles and economic conditions

Bentley et al. find a non-periodic temporal correlation between the average sentiment of English-language books and economic conditions as measured by the Economic Misery Index (EMI, sum of unemployment rate and inflation rate). To test if the periodicity in Chinese-language pop lyrics could be a result of economic cycles, historical data of Taiwan's GDP growth rate, unemployment rate, and inflation rate (CPI, Consumer Price Index) are downloaded from Taiwan's governmental website of National Statistics (https://eng.stat.gov.tw).[1] The reason to choose Taiwan, instead of mainland China or Hong Kong, is because Taiwan has been the leading producer and trendsetter in the Sinophone pop music market (Jones; Moskowitz), and mainland China had not been a major producer until the 2000s.

Figure S1 juxtaposes the standardized yearly average lyric sentiment and Taiwan's standardized annual GDP growth rate. The latter exhibits no clear cyclicity, which is further confirmed by the spectral graph in Figure S2 showing no single, dominant peak. Figure S3 compares the standardized yearly average lyric sentiment and Taiwan's standardized EMI. The latter does display a certain degree of periodicity, but with a period much shorter than 34–35 years—the period of the yearly average lyric sentiment (Wang, Figure 7 "Periodogram of the average lyric sentiment time series"). Spectral graph (Figure S4) reveals a dominant peak at the frequency of 0.0667, corresponding to an estimated period of 15 years for Taiwan's EMI. A periodogram (Figure S5) also confirms an estimated period of 15 years. The significant

[1] The downloaded data are in "Taiwan Misery.xlsx" in this same Dataverse repository.

difference between the two periods (15 vs. 35 years) suggests that the periodicity of lyric sentiment is unlikely to be caused by economic cycles (if any).

At first glance, the lyric sentiment trajectory (blue line in Figure S1) might appear to correspond closely with key developments in mainland China. The marked increase in positive sentiment during the late 1970s seemingly mirrors the collective relief and optimism that followed the conclusion of the Cultural Revolution. Conversely, the decline observed in the 1980s might reflect mounting social pressures as the nation embarked on its early economic reforms. The pronounced emotional low point in the late 1980s seems to align with the societal fallout from the Tian'anmen Square events. Finally, the sustained upswing in positivity from the 1990s through 2010 parallels China's period of rapid economic expansion. However, this "correlation" is mostly spurious: for example, throughout the 1980s, songs by singers from mainland China accounted for less than 15% of all songs released in that era; Taiwan and, secondarily, Hong Kong dominated the scene. Mainland China had not surpassed 25% until the early 2000s. Thus, this trajectory of lyric sentiment cannot mainly be a reflection of the socio-political trends in the mainland (see also Figure S8 and the accompanying discussion below).

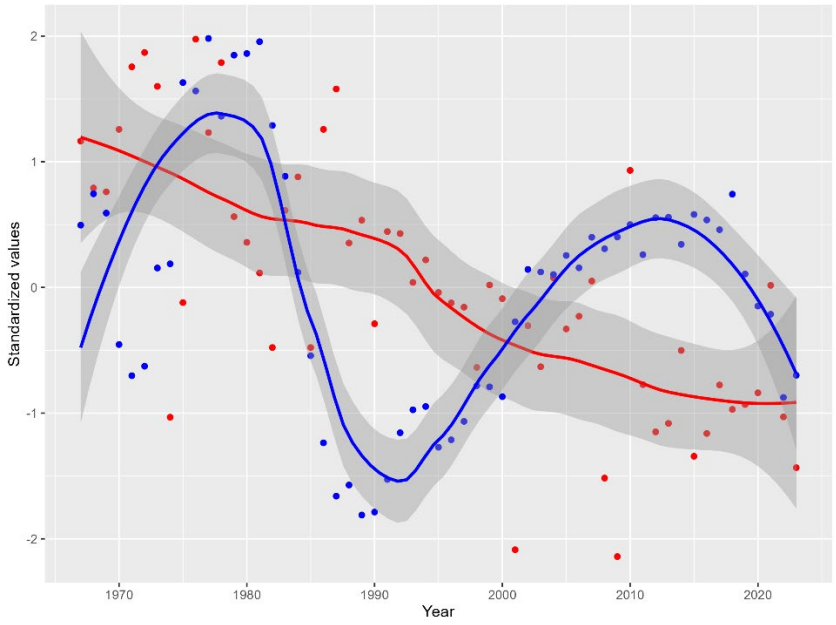

Figure S1. Standardized yearly average lyric sentiment (blue) vs. Taiwan's standardized annual GPD growth rate (red). The grey bands around the curves are the 95% confidence interval for the LOESS-predicted sentiment values (solid lines, span = 0.5).

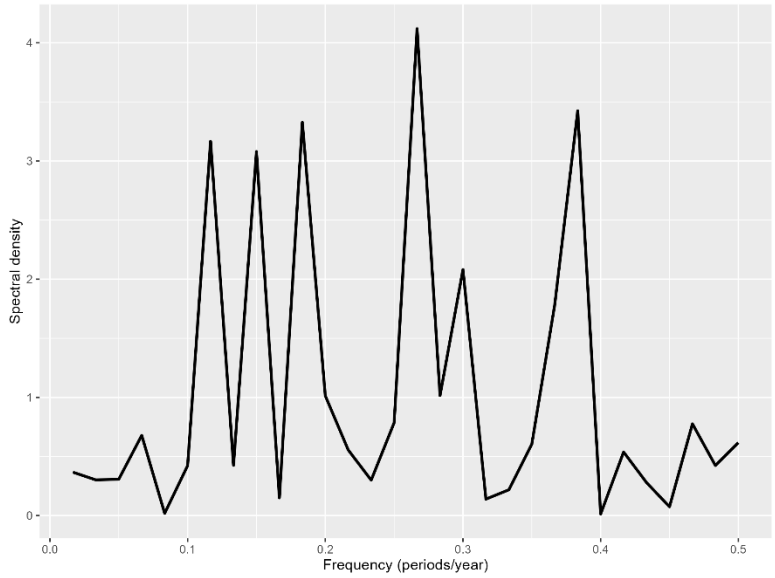

Figure S2. Spectrum of Taiwan's GDP growth rate time series.

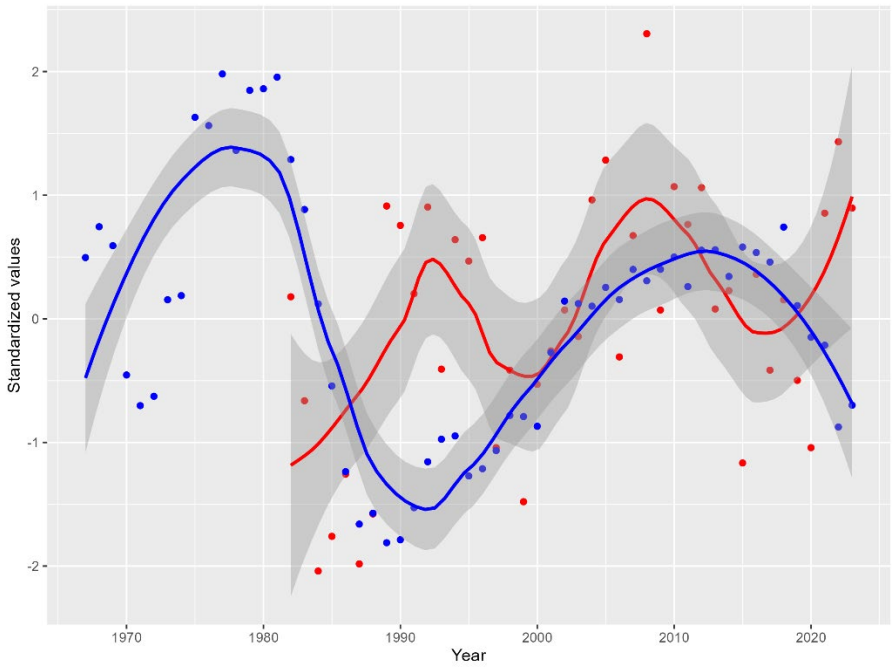

Figure S3. Standardized yearly average lyric sentiment (blue) vs. Taiwan's standardized Economic Misery Index (red). The grey bands around the curves are the 95% confidence interval for the LOESS-predicted sentiment values (solid lines, span = 0.5).

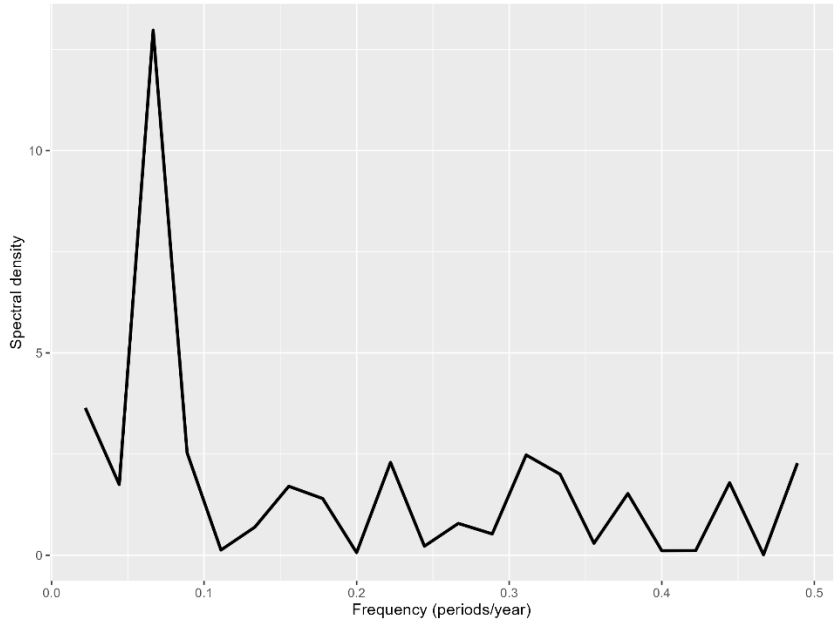

Figure S4. Spectrum of Taiwan's Economic Misery Index time series.

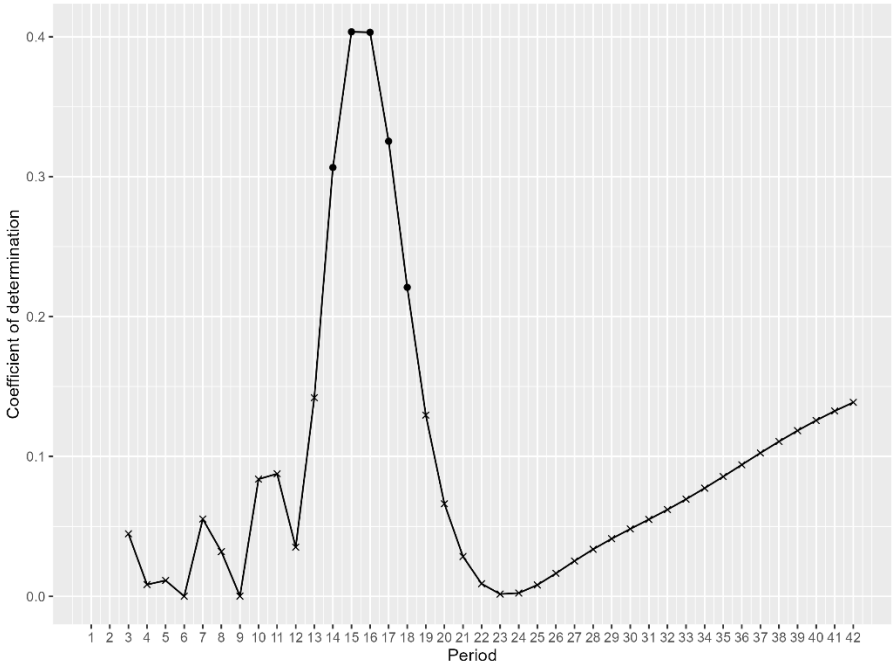

Figure S5. Periodogram of Taiwan's Economic Misery Index time series.

2. Data cleaning and characteristics

For data cleaning, any lyrics that met one or more of the following criteria were excluded: (a) lyrics that were either too short (fewer than 24 Chinese characters, the minimum length of a classical Chinese poem) or too long (exceeding the 4K token context window of ChatGPT 3.5, although this is rare for song lyrics); (b) lyrics containing over 70% non-Chinese characters (indicating too little Chinese content); (c) lyrics produced before 1967 (with fewer than 400 songs annually); (d) lyrics lacking information on their release year; (e) duplicate lyrics, defined as having at least 50% similarity, which were identified using a fuzzy, agglomerative clustering algorithm with functions from Python's "scikit-learn" and "fuzzywuzzy" libraries; and (f) lyrics that does not contain any word included in the emotion lexicon.

Figure S6 presents a logarithmic scale of the number of songs released annually, demonstrating exponential growth. The decline in numbers after 2020 likely reflects a delay in

the website's collection of the most recent songs rather than a drop in production. The sharp decrease in 2023 is also due to the time series ending in mid-July of that year. As for singer types (female, male, and group), Figure S7 shows a dramatic change in the percentages of songs sung by different types: in 1967, 89% songs were sung by female singers, 11% by males, and 0% by groups, whereas in 2020, 31% were sung by females, 55% by males, and 14% by groups, with the gender gap shifting from predominantly female to more male dominant. While the exact cause(s) of this shift has not been determined, it may be partly explained by a rapidly growing female consumer-fan base, who desire more songs sung by "androgynous" male singers (Moskowitz 72, 89).

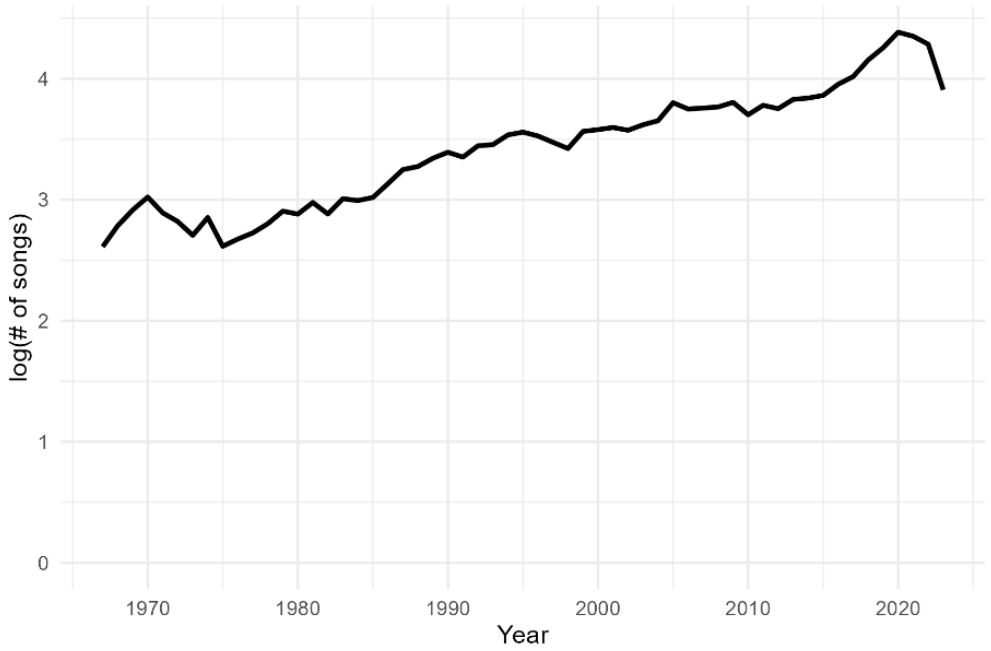

Figure S6. Logarithm of the number of songs released each year.

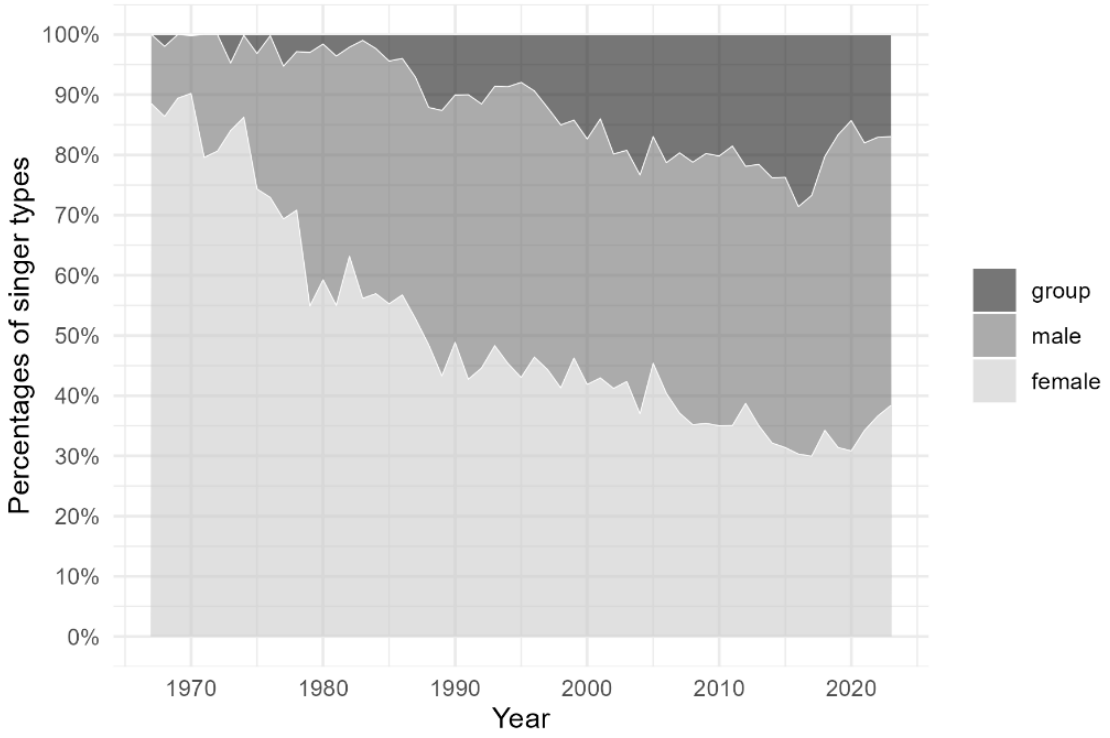

Figure S7. Percentages of songs by different singer types over time.

As for singers' regions, Because the lyric website contains biographical information only for those more well-known singers, about half of all songs—those sung by lesser-known singers—have singers with unidentified regional origins. Moreover, the proportion of songs sung by singers with unknown regions has increased drastically since 2002; for instance, those songs account for around 80% of all the songs released in 2020, as compared with only around 10% in 1980. This trend may be partly explained by the "decentralization" of the pop music industry starting around the early 2000s, when the rise of internet-based channels of music production and distribution facilitated the proliferation of less popular, independent artists. Among those songs by singers with identifiable regional origins, Taiwan consistently accounted for around 50% throughout the period under study, while mainland China had not surpassed 25% until the early 2000s, but since then, the mainland has been the runner-up, replacing Hong Kong. Figure S8 shows the LOESS-smoothed, yearly average total sentiment scores (obtained via the ChatGPT-

assisted approach) of lyrics by regions, using songs by singers with identifiable regional origins only (supposedly, singers who are better-known). It shows that all three major Sinophone regions—Taiwan, Hong Kong, and mainland China—have been following similar sentiment trends since 1980 (when the mainland opened up), confirming the highly integrated nature of the Sinophone pop music market, with Taiwan being the leading trendsetter and producer (Moskowitz, 2010). Moreover, the amplitude of the sentiment oscillation is the greatest in Taiwan, second in Hong Kong, and smallest in mainland China—a pattern consistent with the hypothesis that the sentiment dynamics originated in Taiwan, cascaded to Hong Kong, and then rippled across the mainland. However, since about half of the songs in our dataset have singers with unidentifiable regional origins, we cannot perform conclusive testing of the hypothesis without improved meta-data.

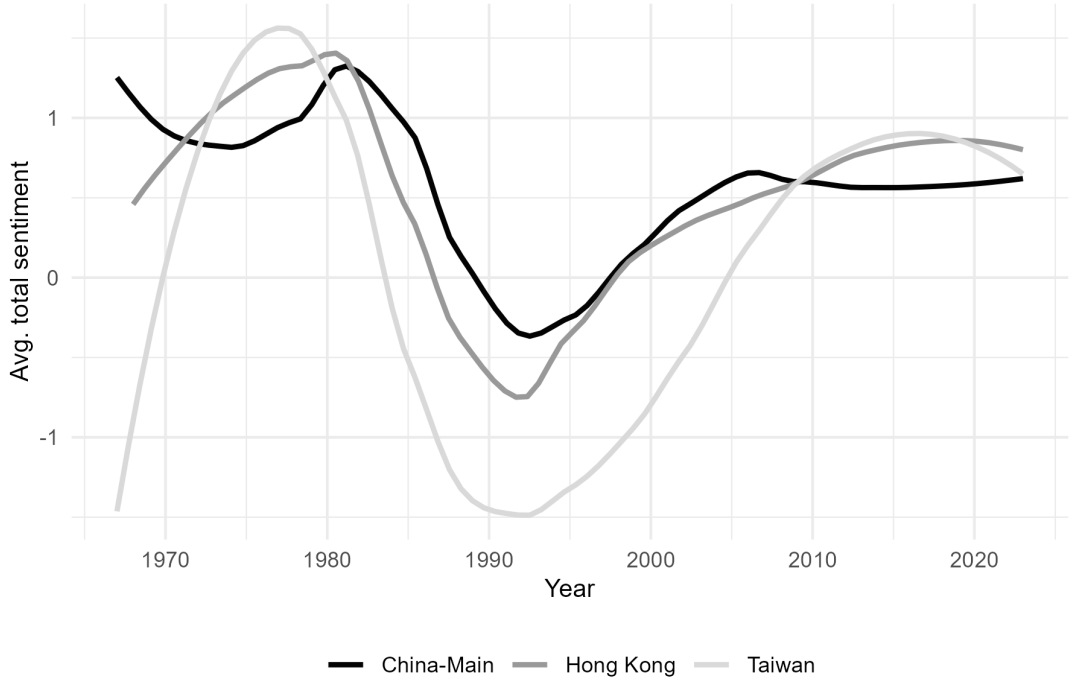

Figure S8. LOESS-smoothed (span = 0.5) yearly average total sentiment scores of lyrics by singers' regions (ChatGPT-assisted).

3. Rationale for choosing three ChatGPT-output emotion words

The rationale for deciding to choose exactly three emotion words for every lyric is based on repeated experiments. For each round of experiment, 1,000 lyrics are randomly selected from the dataset and fed to ChatGPT, which is asked to output Chinese emotion words to capture the major emotions in each song, without imposing any explicit limit on the number of emotion words to be output. Then, look at the distribution of the number of ChatGPT-output emotion words from the 1,000 lyrics. The resulting distributions are very consistent, over 50% of songs output exactly 3 emotion words, around 30% of songs output 4 emotion words, less than 10% output 5 words, and the rest 10% output 2 words. Three is at once the median, mean, and mode. Additionally, by forcing ChatGPT to output three emotion words for lyrics that would initially result in two or four words, this approach helps break "ties" when there is an equal number of positive and negative emotion words, compelling ChatGPT to identify the predominant sentiment—either positive or negative—of each lyric.

4. Developing the emotion lexicon from the CSVOL

The CSVOL's (Chinese Sentiment Vocabulary Ontology Library) emotion categories are structured according to Paul Ekman's framework of basic emotions (Ekman). Ekman posits that some emotions qualify as more fundamental than others, and specific criteria can be established to set these emotions apart. Based on this theory, there are six basic emotions—*anger*, *fear*, *sadness*, *enjoyment*, *disgust*, and *surprise.* Within this structure, however, Xu et al. refine the *enjoyment* category by splitting it into *joy* 乐 and *liking* 好, thereby introducing a total of seven emotion categories. These seven categories are further partitioned into twenty-one subcategories (see Table S1).

Table S1. Emotion classification of the original CSVOL

	Emotions	Sub-emotions	Labels
1	Joy 乐	Happiness 快乐	PA
2		Contentment 安心	PE
3	Liking 好	Respect 尊敬	PD
4		Praise 赞扬	PH
5		Trust 相信	PG
6		Fondness 喜爱	PB
7		Wishing 祝愿	PK
8	Anger 怒	Anger 愤怒	NA
9	Sadness 哀	Sorrow 悲伤	NB
10		Disappointment 失望	NJ
11		Guilt 疚	NH
12		**Missing/Longing 思**	**PF**
13	Fear 惧	Panic 慌	NI
14		Dread 恐惧	NC
15		Shame 羞	NG
16	Disgust 恶	Annoyance 烦闷	NE
17		Aversion 憎恶	ND
18		Criticism 贬责	NN
19		Envy 妒忌	NK
20		Doubt 怀疑	NL
21	Surprise 惊	**Surprise 惊**	**PC**

Generally speaking, a sub-emotion with a label beginning with the letter "N" has a negative valence, and one with a label beginning with "P" has a positive valence ($v = 1$).[2] However, there are two exceptions that make the CSVOL emotion categorization inconsistent, which need to be addressed. The first is the subcategory *jing* 惊 (surprise), with the label "PC"; there are, however,

[2] In CSVOL, a word's emotional valence needs to be distinguished from its "polarity." Polarity as defined by Xu et al. means the implied judgmental attitude (commendatory or derogatory) associated with that word (182). Although a word with a negative (or positive) valence usually has a derogatory (or commendatory) tone, this is not always the case in CSVOL. For example, while the Chinese idiom *shoutou jin* 手头紧 (being financially tight) has a negative valence as it pertains to the emotion subcategory *fanmen* 烦闷 (irritated and depressed), its assigned polarity is 0 (neutral, not -1, derogatory), because people usually do not morally judge the state of being financially tight. Therefore, using polarity to substitute for valence could engender inaccuracies in sentiment measurement.

bad surprises (e.g., *zhenjing* 震惊, shock) and good ones (e.g., *jingxi* 惊喜, pleasant surprise). To separate the negative from the positive, we split it into two new subcategories: "shock" (NPC) for the negative and "amazement" (PC) for the positive.

The second exception is the subcategory *si* 思 (missing/longing) within the *sadness* category: despite its negative-sounding name, the label for the *si* subcategory is "PF," and many words in it do have a positive valence. To distinguish positive "longing" (e.g., *panwang* 盼望, look forward to) from negative "missing" (e.g., *dan xiangsi* 单相思, unrequited love), we split the subcategory into two: a new subcategory "missing" (NPF) is created to label those negative words, and the rest of the positive words retain the "longing" (PF) label. However, a logical consequence of this modification is that the new, positive "PF" subcategory cannot be kept within the *sadness* category. To address this, we move the new "longing" (PF) subcategory to the *liking* category. Now, there are in total 23 subcategories.

To further expand the CSVOL, synonyms of original word entries are added to the lexicon as new entries, carrying over the same emotional properties as the original entries. These synonyms are sourced from a collection compiled using the online Chinese thesaurus *Baidu Hanyu* (Keson96). After expansion, the lexicon includes a total of 38,237 words.[3]

5. Evaluating the ChatGPT-assisted approach vs. the lexicon-only method

We randomly selected and manually annotated 200 lyrics for their respective overall sentiment (positive or negative). The results are then used as the standard to evaluate and compare the predictive accuracy and performance of the ChatGPT-assisted and the lexicon-only methods.[4]

[3] The reshaped original CSVOL lexicon is in "DLUT_reshaped_final.csv," while the expanded version that includes synonyms is in "DLUT_reshaped_final_Synonym_expanded.csv" in the repository.
[4] The sample and evaluation data are in "manual check.xlsx" in the repository.

Table S2 displays the predictive accuracy of both methods, which shows that the ChatGPT-assisted approach has not only a much higher accuracy (87% vs. 64%) but also a much more balanced distribution between false positives and false negatives. In contrast, the lexicon-only method has a rather high rate of false positives. Table S3 exhibits the standard metrics for the predictive performance of both methods: the higher the numbers, the better the performance (Goutte & Gaussier). "Macro average" is the arithmetic mean of the performance metrics of the positive and negative classes. The results show the ChatGPT-assisted method performs much better across all metrics.

Table S2. Prediction accuracy: ChatGPT-assisted vs. lexicon-only (numbers are counts)

	ChatGPT-assisted	Lexicon-only
Correct	174 (87%)	128 (64%)
False positive	16	59
False negative	10	13

Table S3. Performance metrics: ChatGPT-assisted vs. lexicon-only

	ChatGPT-assisted			Lexicon-only		
	Positive	Negative	Macro avg.	Positive	Negative	Macro avg.
Precision	0.84	0.90	0.87	0.58	0.79	0.68
Recall	0.89	0.85	0.87	0.86	0.45	0.65
F1-score	0.86	0.88	0.87	0.69	0.57	0.63

6. Analytical solutions to the DHO model

This section provides the derivation of the analytical solution to equation (7) for damped harmonic oscillation: $d^2s/dt^2 + 2\beta \cdot ds/dt + \omega^2 s = 0$. Assume, without loss of generality, that at time $t = 0$, $s(0) = A_0$ ($A_0 \in \mathbb{R}$) and $ds/dt|_{t=0} = 0$. Equation (7) indicates that a linear combination of $s(t)$, ds/dt, and d^2s/dt^2 is equal to zero for all *t*, which in turn suggests that an ansatz is of the form $s(t) = A_0 e^{\lambda t}$, where $\lambda \in \mathbb{C}$ (the set of complex numbers). Plugging this ansatz into equation (7) yields

$$(\lambda^2 + 2\beta\lambda + \omega^2)A_0 e^{\lambda t} = 0, \text{ with } \beta, \omega > 0. \tag{A1}$$

Since this equation holds for all *t*, it follows that $\lambda^2 + 2\beta\lambda + \omega^2 = 0$, which is the "characteristic equation" of the differential equation. From the quadratic formula, solving for λ gives

$$\lambda_1 = -\beta - \sqrt{\beta^2 - \omega^2}, \text{ and } \lambda_2 = -\beta + \sqrt{\beta^2 - \omega^2}. \tag{A2}$$

Then, the general solution to equation (7) can be written as

$$s(t) = A_1 e^{\lambda_1 t} + A_2 e^{\lambda_2 t}, \tag{A3}$$

where A_1 and $A_2 \in \mathbb{C}$ are two arbitrary constants.

If the damping ratio $\beta/\omega > 1$ (over-damping), λ_1 and λ_2 are both negative real numbers, which means both terms in equation (A3) are diminishing exponentially over time. Now consider the case where $\beta/\omega \gg 1$, using Taylor Expansion:

$$\sqrt{\beta^2 - \omega^2} = \beta\left(1 - \frac{\omega^2}{\beta^2}\right)^{\frac{1}{2}} \approx \beta\left(1 - \frac{1}{2}\frac{\omega^2}{\beta^2}\right) = \beta - \frac{\omega^2}{2\beta}. \tag{A4}$$

Substituting equation (A4) into (A2) gives $\lambda_1 \approx -\omega^2/2\beta$ and $\lambda_2 \approx -2\beta + \omega^2/2\beta$. Because $|\lambda_2| \gg |\lambda_1|$ (easy to verify), the second term in equation (A3) diminishes much faster than the first term. It follows that, with the initial condition $s(0) = A_0$, as time *t* passes, the first term quickly becomes dominant:

$$s(t) \approx A_0 e^{-\frac{\omega^2}{2\beta}t}, \tag{A5}$$

which is equation (8) for over-damping.

If the damping ratio $\beta/\omega = 1$ (critical damping), the characteristic equation has repeated real roots: $\lambda_1 = \lambda_2 = -\beta$. In this case, it is easy to verify that, in addition to $e^{-\beta t}$, the form $te^{-\beta t}$ is also a solution to equation (7). Then, the general solution can be written in the form below,

$$s(t) = A_1 e^{-\beta t} + A_2\left(te^{-\beta t}\right) = (A_1 + A_2 t)e^{-\beta t}. \tag{A6}$$

Given the initial condition $ds/dt|_{t=0} = 0$, and from equation (A6), we have

$$\left.\frac{ds}{dt}\right|_{t=0} = (-\beta A_1 - \beta A_2 t + A_2)e^{-\beta t}\big|_{t=0} = -\beta A_1 + A_2 = 0. \quad \text{(A7)}$$

Also, $s(0) = A_1 = A_0$ (the other initial condition). Then, we have $A_1 = A_0$ and $A_2 = \beta A_0$. Plugging these into equation (A6) yields

$$s(t) = (1 + \beta t)A_0 e^{-\beta t}, \quad \text{(A8)}$$

which is equation (9) for critical damping. This is a monotonously decreasing function (if $A_0 > 0$), because $ds/dt = -A\beta^2 t e^{-\beta t} < 0$, for all $t > 0$. In addition, $\lim_{t\to\infty} s(t) = \lim_{t\to\infty} \frac{A(1+\beta t)}{e^{\beta t}} = \lim_{t\to\infty} \frac{A}{e^{\beta t}} = 0$ (L'Hôpital's Rule).

If the ratio $\beta/\omega < 1$ (under-damping), the characteristic equation has two complex roots $\lambda_1 = -\beta - i\sqrt{\beta^2 - \omega^2}$, and $\lambda_2 = -\beta + i\sqrt{\beta^2 - \omega^2}$. Substituting these into equation (A3) results in

$$s(t) = e^{-\beta t}(A_1 e^{-i\sqrt{\beta^2-\omega^2}t} + A_2 e^{i\sqrt{\beta^2-\omega^2}t}). \quad \text{(A9)}$$

Because $s(t)$ is always a real number at any time *t*, we have $s(t) = \overline{s(t)}$, where $\overline{s(t)}$ is the complex conjugate of $s(t)$. Following the operational rules of complex conjugate, we have

$$\begin{aligned}\overline{s(t)} &= \overline{e^{-\beta t}\left(A_1 e^{-\imath\sqrt{\beta^2-\omega^2}t} + A_2 e^{\imath\sqrt{\beta^2-\omega^2}t}\right)} \\ &= \overline{e^{-\beta t}}\left(\overline{A_1}\cdot\overline{e^{-\imath\sqrt{\beta^2-\omega^2}t}} + \overline{A_2}\cdot\overline{e^{\imath\sqrt{\beta^2-\omega^2}t}}\right) \\ &= e^{-\beta t}\left(\overline{A_1}\cdot e^{i\sqrt{\beta^2-\omega^2}t} + \overline{A_2}\cdot e^{-i\sqrt{\beta^2-\omega^2}t}\right). \quad \text{(A10)}\end{aligned}$$

Since equations (A9) and (A10) are always equal, by comparing the corresponding terms in the two equations, we have $\overline{A_1} = A_2$, which means A_1 and A_2 are a conjugate pair. Then rewrite A_1, A_2 as $A_1 = re^{i\varphi}$, $A_2 = re^{-i\varphi}$, with $r, \varphi \in \mathbb{R}$, and substitute these into equation (A9):

$$s(t) = e^{-\beta t}\left(re^{i\varphi}\cdot e^{-i\sqrt{\beta^2-\omega^2}t} + re^{-i\varphi}\cdot e^{i\sqrt{\beta^2-\omega^2}t}\right)$$

$$= re^{-\beta t}\left(e^{-i\left(\sqrt{\beta^2-\omega^2}t-\varphi\right)} + e^{i\left(\sqrt{\beta^2-\omega^2}t-\varphi\right)}\right). \quad \text{(A11)}$$

Applying Euler's formula $e^{ix} = \cos(x) + i\cdot\sin(x)$ leads to $e^{ix} + e^{-ix} = 2\cos(x)$, and applying this to equation (A11) yields

$$s(t) = 2r\cdot e^{-\beta t}\cos\left(\sqrt{\beta^2-\omega^2}t-\varphi\right)$$

$$= Ae^{-\beta t}\cos\left(\frac{2\pi}{T}t-\varphi\right), \text{ with } A \triangleq 2r,\ T \triangleq \frac{2\pi}{\sqrt{\omega^2-\beta^2}}, \quad \text{(A12)}$$

which is equation (10) for under-damping.

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