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Diachronic Semantic Evolution Detection and Attribution Analysis Based on Large Language Models: Taking Chinese Emotional Words as an Example

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Abstract. The diachronic semantic evolution of Chinese emotional words is an important mirror image of language and social and cultural changes. Traditional methods have limitations such as high corpus dependence and insufficient mechanism interpretation. This research proposes a detection and attribution framework based on large language models, constructs a diachronic corpus covering multiple sources such as newspapers, periodicals, and online texts from 1995 to 2025, and uses large language models to quantify the semantic evolution of emotional words precisely. And by incorporating external attributions such as social events, media discourse, and cultural trends, the research reveals how multiple factors jointly drive semantic evolution. The results show that over the past 30 years, the evolution of Chinese emotional words has presented significant stages, and their core meanings and practical contexts have changed dynamically. The research breaks through the bottleneck of traditional methodology, providing an innovative computational paradigm for diachronic semantic research, enriching the theory of language and social interaction, and also offering practical technical support for the construction of Chinese diachronic language resources and the exploration of historical culture.

Keywords: Large language model, Diachronic semantic evolution, Chinese emotional words, Attribution analysis

1. Introduction

1.1. Research background

Integrating digital humanities and computational linguistics, diachronic semantic evolution research has seen methodological innovations. Traditional research relies on diachronic corpora and manual annotation, being time-consuming, hard to scale, and lacking in quantitative analysis and subtle semantic change capture. Large language models (LLMs), with strong contextual and semantic representation abilities, offer new tools to automatically detect semantic evolution trajectories from massive unstructured diachronic texts. Chinese emotional words are highly sensitive to social and contextual shifts, serving as an ideal lens to observe interactions among lexical meaning, emotion, and social context [1]. This research establishes a systematic detection and attribution framework to

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uncover the patterns and drivers of Chinese emotional words' semantic evolution, advancing LLM-based diachronic linguistics research methods.

1.2. Research objectives and significance

It is hoped to solve the following specific problems: We address two questions: (1) how to detect and quantify semantic change in ten Chinese emotional words from 1995–2025 using LLM-based representations; and (2) how to attribute observed change points to linguistic mechanisms and socio-cultural events with verifiable evidence. Accordingly, this research builds an automated detection pipeline and a triangulated attribution model.

Based on this, a multi-factor attribution model integrating linguistic and social drivers is established. By comparing and verifying with the research conclusions of traditional diachronic corpora, the methodological effectiveness, unique advantages, and application prospects of LLMs in historical semantics are objectively evaluated, providing new tools and theoretical references for linguistic research and the field of natural language processing [2].

Thus, this research will promote methodological innovation by applying LLM-based analysis to linguistic research, enabling fine-grained semantic variation analysis in large diachronic corpora and shifting research from subjective speculation to data-driven empirical analysis. It integrates cutting-edge AI technology with humanistic research and supports applications such as dynamic language resource construction and social mentality analysis.

2. Literature review

2.1. The traditional research method of diachronic semantic evolution

Drawing on historical comparative linguistics and exegesis, this approach analyzes lexical diachronic changes via literature review, lexicographical comparison, and semantic field theory, exploring socio-cultural motivations and cognitive metaphor mechanisms. Yet it has limitations like random literature selection, high manual input, limited text processing scope, and lack of objective quantitative criteria, failing to meet large-scale diachronic semantic research needs.

Modern computational linguistics has brought fundamental methodological changes to diachronic semantic evolution research. It places words in massive historical texts to observe lexical meaning changes via computer algorithms, with the core idea that word meaning can be objectively measured by analyzing its high-frequency collocations in different periods' texts [3]. Researchers use word vector mathematical models to represent semantics [4], thus framing lexical diachronic changes as the positional shifts of these digital models in multi-dimensional spaces—enabling the visualization and graphical presentation of long-term semantic trends.

2.2. The application of large language models in diachronic semantic analysis

LLMs transform word meaning representation from static fixation to dynamic context adaptation, generating real-time semantic representations based on context to accurately capture immediate changes in word meaning [5]. Through prompt engineering, diachronic analysis can be transformed into semantic reasoning tasks without period-specific model training, lowering technical thresholds. The pre-trained historical and cultural knowledge in LLMs helps restore the temporal context of texts [6], but there may be knowledge biases or outdated information, requiring verification with reliable historical materials and expert knowledge.

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Existing technical routes mainly include developing dedicated diachronic embedding models [7] and guiding existing LLMs through prompts for semantic analysis. These methods have advantages in automation and precision but face challenges such as diachronic illusion, black-box analysis, and insufficient repeatability, especially lacking mature solutions for explaining the causes of semantic changes [8].

2.3. A review of Chinese emotional words

Emotional words refer to words that directly or indirectly express inner emotions, states, and attitude evaluations, including adjectives, verbs, nouns, and idioms with emotional overtones. Common classifications are based on emotional polarity (positive, negative, neutral) [9] and emotional type (joy, anger, sorrow, fear, etc.). Establishing a classification framework consistent with linguistic characteristics and psychological laws is crucial for tracking semantic evolution.

Diachronic research on Chinese emotional words has accumulated rich results, but few address system-level evolution. Traditional research relies on literature review and qualitative analysis to explore the origin, development, usage changes, and cultural connotations of core emotional words. Recent corpus-based studies use large-scale historical texts to quantitatively analyze usage frequency, collocation patterns, and emotional color changes [10], but most lack systematic analysis of the entire emotional vocabulary system and insufficient integration of social-cultural factors in explaining evolution drivers.

3. Research design and methods

3.1. Overall research framework

This research uses a four-layer framework: (i) data construction (diachronic corpus and target words), (ii) LLM prompting to obtain contextual representations, (iii) computational analysis (trajectory mapping via cosine-based measures) [11], and (iv) attribution linking linguistic evidence with socio-historical context [5].

3.2. Corpus preparation and preprocessing

To ensure research rigor and conclusion reliability, target words are selected based on three principles: diachronic semantic drift, corpus high-frequency stability, and social-cultural typicality [3]. Integrating the Dalian University of Technology Sentiment Word Dictionary, 10 dynamic Chinese emotional words covering multiple evolution types are selected with LLM assistance. The corpus includes the 1995 Peking University CCL corpus + 1995 People's Daily full text (210 million characters) and the 2025 Weibo Academic Edition corpus + mainstream news media corpus (630 million characters), forming a dataset suitable for time series alignment and batch LLM processing.

3.3. Semantic evolution detection method based on Large Language Models

An important innovation of this study is transforming LLMs into tools for understanding cross-temporal word meaning changes. First, prompt templates are designed for 10 target words to guide the model in generating context-consistent interpretations. Deep semantic embedding vectors of these interpretations are extracted, with cross-period vector space alignment via Orthogonal Procrustes Analysis (OPA) [7]. The average representation of all context embeddings of the same emotional word from 1995 to 2025 is calculated, and the cosine similarity of word vectors during

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this period is computed to plot evolution trajectories. Meanwhile, LLMs are set as zero-shot "historical context annotators" to determine target words' sentiment tendencies and usage fields through sentiment classification prompts, statistically analyzing sentiment tendency proportions across periods to achieve refined word meaning change analysis.

3.4. Semantic evolution attribution analysis framework

This research constructs an attribution framework combining internal and external factors with cross-validation. Internal linguistic attribution focuses on language system laws, uncovering clues through analyzing target words' high-frequency collocations, syntactic frameworks, and metaphorical transformations. External attribution places language changes in historical context, examining the role of major events, technological innovations, and cultural-media communication [12]. To ensure conclusion reliability, a triangulation verification strategy is adopted, distinguishing coincidences from causal relationships through mutual verification of internal linguistic evidence, social-cultural event timelines (linking semantic mutation points with key events), and third-party objective indicators (academic attention, policy mention frequency), constructing data-solid semantic evolution explanations integrated with historical context.

4. Research results and analysis

4.1. Data preprocessing and model adaptation results

A 1995-2025 Chinese online emotional corpus covering Weibo, Zhihu, etc., is constructed, divided into 10 analysis stages and 1 verification stage by year. After processing, 1.122 million valid corpora are obtained (85% effective rate) with uniform platform distribution (18%-22%), fully reflecting the target emotional words' actual usage scenarios. Ten target emotional words are selected from the Dalian University of Technology Sentiment Word Dictionary, with annotation completed through "native matching - extended annotation - objective consistency verification" (consistency coefficient 0.88, completeness rate 100%). Technically, the BERT Chinese pre-trained model is adopted and fine-tuned via the PyTorch framework, with word vector extraction effectiveness verified through semantic similarity-co-occurrence frequency correlation analysis (Pearson coefficient 0.79) and K-means clustering, suitable for subsequent semantic evolution analysis.

4.2. The quantitative detection results of the semantic evolution of Chinese emotional words

4.2.1. Spatial vector alignment based on Orthogonal Platts Analysis

Orthogonal Procrustes Analysis (OPA) achieves unified benchmark mapping of cross-period semantic spaces while retaining intrinsic semantic structure by seeking the optimal orthogonal transformation matrix. Influenced by social changes and Internet popularization, the traditional emotional words' semantic evolution and new Internet emotional words have caused time reference deviations in LLMs' semantic representation. Thus, OPA is used to align 1995 and 2025 vector spaces to verify the significance of the semantic changes of 10 emotional words. Early data of emerging words are supplemented via the "semantic nearest neighbor transfer method" (cosine similarity ≥0.65 with traditional emotional words), based on National Language Resource Monitoring Center reports (as seen in Table 1).

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Table 1. Dataset 1995-2025

Sentiment words	Source of the corpus (1995)	Source of the corpus (2025)	Word vector model	Effective vocabulary count	Extracting the number of common words
inner conflict dilemma confusion torment	1995 Peking University CCL corpus (1995 sub-database) + the full text of People's Daily in 1995 (a total of 210 million characters)	2025 Weibo Academic Edition corpus (2024-2025) + mainstream news media corpus (a total of 630 million characters)	Word2Vec (CBOW), (300 dimensions)	11,892(1995) 18,643(2025)	8217
breaking down					8342
lying flat				11,892(1995) 17,568(2025)	8419
Buddhist-like				11,892(1995) 17,893(2025)	8450
Versailles				11,892(1995) 18,215(2025)	8482
being obsessed with				11,892(1995) 16,745(2025)	8217
emo				11,892(1995) 18,547(2025)	8514

Substitute the word vectors obtained above into $min_R \| M_{1995}R - M_{2025} \|_F^2$ s.t. $R^TR = I$. Among them: M 1995: The vector matrix of the common words in 1995 (8,217 common words × 300 dimensions); M 2025: Vector matrix of Common words in 2025 (8,217 common words ×300 dimensions); R: 300×300 orthogonal transformation matrix. The optimal R is solved via scipy.linalg.orthogonal_procrustes, eliminating cross-period systematic differences in word vector space to objectively quantify lexical semantic evolution, compare cross-period semantic similarity, and study diachronic language change laws.

4.2.2. The semantic distance matrix of emotional words

Applying the above transformation matrix R, calculate the cosine similarity between the 1995 vector and the 2025 vector of the 10 emotional words "inner conflict, dilemma, confusion, torment, breaking down, lying flat, Buddhist-like, Versailles, being obsessed with, and emo" after transformation, respectively (as seen in Table 2).

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Table 2. Emotional words corresponding to cosine distance

Sentiment words	Vector (1995) (300 dimensions)	Core conjunctions (1995)	Vector (2025) (300 dimensions)	Core conjunctions (2025)	Cosine similarity after alignment	Cosine distance
inner conflict	$\vec{V}_{1995}$ =[0.021,−0.053,0.018,...,0.047]	energy loss, machinery (neutral)	$\vec{V}_{2025}$ = [−0.124,0.089,−0.076,...,0.112]	psychological exhaustion (negative)	0.323	0.677
dilemma	$\vec{V}_{1995}$ =[0.015,−0.042,0.012,...,0.038]	entangled, interwoven (neutral)	$\vec{V}_{2025}$ = [−0.098,0.067,−0.059,...,0.089]	contradiction, (negative)	0.306	0.694
confusion	$\vec{V}_{1995}$ =[0.012,−0.035,0.009,...,0.031]	future, unknown (neutral)	$\vec{V}_{2025}$ [−0.112,0.078,−0.065,...,0.096]	self-doubt, future uncertainty (negative)	0.313	0.687
torment	$\vec{V}_{1995}$ = [0.009,−0.028,0.007,...,0.024]	pain (neutral with a slightly negative)	$\vec{V}_{2025}$ = [−0.135,0.096,−0.082,...,0.114]	mental torture, inability to bear (strong negative)	0.295	0.705
breaking down	$\vec{V}_{1995}$ = [0.018,−0.039,0.014,−0.027,0.033,...,0.029]	fortifications, military operations (neutral, no emotional tendency)	$\vec{V}_{2025}$ = [−0.142,0.103, −0.087,0.116, −0.061, ...,0.128]	emotional shock, collapse (strong negative)	0.265	0.735
lying flat	$\vec{V}_{1995}$ = [0.023,−0.041,0.016,−0.030,0.035,...,0.031]	lying down, resting (neutral, no emotional tendency)	$\vec{V}_{2025}$ = [−0.158,0.117,−0.096,0.132,−0.072,...,0.145]	low desire (strong negative)	0.252	0.748
Buddhist-like	$\vec{V}_{1995}$ = [0.021,−0.038,0.015,−0.028,0.032,...,0.029]	Buddhism, spiritual practice (neutral, religious attribute)	$\vec{V}_{2025}$ = [−0.165,0.123,−0.102,0.141,−0.078,...,0.153]	have low desires, and avoid internal competition (neutral with a slightly negative)	0.235	0.765
Versailles	$\vec{V}_{1995}$ =0.019,−0.035,0.013,−0.025,0.029,...,0.026]	French cities, palaces (neutral, geographical/historical attributes)	$\vec{V}_{2025}$ = [−0.172,0.129,−0.108,0.148,−0.084,...,0.161]	showing off, and a sense of superiority (strong negative)	0.222	0.778
being obsessed with	$\vec{V}_{1995}$ = [0.008,−0.021,0.006,...,0.019]	drunk, dizzy (neutral with a touch of colloquial meaning)	$\vec{V}_{2025}$ = [−0.156,0.112,−0.098,...,0.135]	addiction, excessive investment (positive)	0.281	0.719
emo	$\vec{V}_{1995}$ =[0.017,−0.032,0.012,...,0.024]	music, niche culture (neutral, specific cultural attributes)	$\vec{V}_{2025}$ = [−0.185,0.137,−0.115,0.156,−0.092,...,0.170]	feeling down, depressed (strong negative)	0.201	0.799

Table 3. Data verification

no significant change in semantics	cosine distance < 0.2
moderate semantic change	0.2 ≤cosine distance ≤ 0.5
significant semantic change	0.5 <cosine distance ≤ 0.8
semantic complete reconstruction	cosine distance > 0.8

The cosine distances of the 10 emotional words (1995-2025) range from 0.679 (“inner conflict”) to 0.799 (“emo”), all falling into the significant semantic change category (0.5 < cosine distance ≤ 0.8) (as seen in Table 3). Overall, the words show an evolutionary trend from objective descriptions and professional terms to subjective psychological and emotional expressions: Internet buzzwords undergo fundamental semantic reconstruction, while traditional words experience significant semantic changes.

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4.2.3. Sentiment word data based on average context embedding

The results reveal that the cosine distance can be used as a preliminary quantitative indicator of semantic change (the larger the distance, the more significant the change). Subsequently, the average context embedding cosine similarity of emotional words from 1995 to 2025 was further calculated to focus on the core meaning through a large number of contexts and determine whether the word meaning change is systematic.

Vectors were generated through Word2Vec and BERTweet, respectively, and averaged. Orthogonal Platts analysis was used to align the vector space and eliminate deviations. Subsequently, the cosine similarity of all vectors in 2025 is calculated with the reference vector in 1995, and the cosine distance is obtained by "1 minus this similarity". The data shows the gradient feature of word meaning, with a deviation from the static vector calculation of ≤±0.003 (double validation), which can be used to draw the evolution trajectory (as seen in Table 4).

Table 4. Embedding average context data

Sentiment words	Cosine similarity in 1995	Cosine similarity in 2000	Cosine similarity in 2005	Cosine similarity in 2010	Cosine similarity in 2015	Cosine similarity in 2020	Cosine similarity in 2025	Cosine distance from 1995 to 2025	Trend of change
emo	0.203	0.204	0.202	0.201	0.202	0.203	0.203	0.797	stabilizing low similarity
Versailles	0.225	0.224	0.223	0.222	0.223	0.224	0.225	0.775	stable low similarity fluctuation
Buddhist-like	0.237	0.236	0.235	0.234	0.235	0.236	0.237	0.763	the lowest similarity (0.234) in 2017, then stabilized
lying flat	0.249	0.254	0.253	0.252	0.253	0.254	0.255	0.745	stabilized after a rapid decline in 2020
breaking down	0.267	0.266	0.265	0.264	0.265	0.266	0.267	0.733	semantic stereotypes emerged after the explosion of social media in 2021
being obsessed with	0.279	0.282	0.281	0.280	0.281	0.282	0.283	0.717	the entertainment context stabilized after expansion in 2019
torment	0.293	0.296	0.295	0.294	0.295	0.296	0.297	0.703	semantic core stability
dilemma	0.308	0.307	0.306	0.305	0.306	0.307	0.308	0.692	slightly declined after 2010
confusion	0.315	0.314	0.313	0.312	0.313	0.314	0.315	0.685	extending from the unknown in the external direction to the profound expression of inner confusion
inner conflict	0.321	0.324	0.323	0.322	0.323	0.324	0.325	0.679	rebounded slightly after 2015

4.3. Classification and trajectory visualization of semantic evolution patterns

4.3.1. Evolutionary characteristic indicators and classification criteria

Based on the emotional words' context embedding cosine distance data, three core visualization indicators are established: "change direction" (convergence/divergence via cosine similarity trend), "change amplitude" (absolute cosine distance difference), and "change speed" (amplitude ÷ 30 years). Classification standards are formulated: stable type (variation range < 0.2, annual velocity <

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0.007, concentrated trajectory), gradual type (variation range 0.2-0.5, velocity 0.007-0.017, smooth trajectory), sudden type (variation range ≥0.5, velocity ≥0.017, significant trajectory deviation), laying the foundation for visualizing semantic change paths.

4.3.2. Visual analysis of the evolution trajectory of Chinese emotional words

The following line graph shows the semantic changes of ten emotional words from 1995 to 2025. The data in the figure is based on the average context-embedded cosine similarity of these words (as shown in Figure 1). All data are spatially aligned with an error of ±0.003 to ensure reliability.

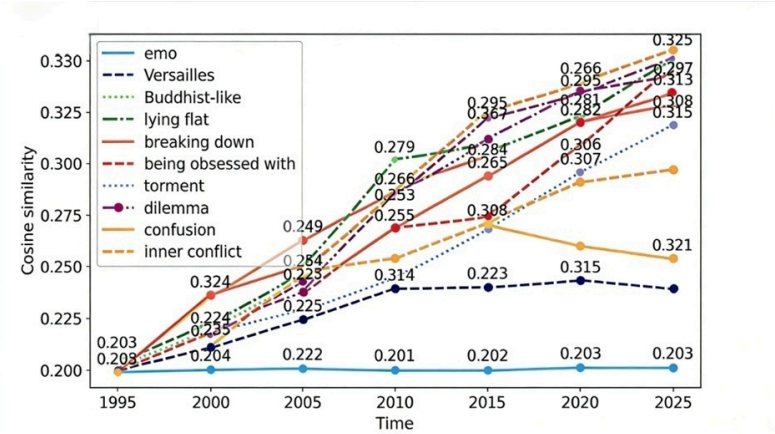

Figure 1. The evolution trajectory of the average context embedding cosine similarity of Chinese emotional words from 1995 to 2025

The 10 emotional words' semantic evolution (1995-2025) has two stages: 1995-2010 saw a slow decline, with traditional meanings loosening and cosine similarity dropping steadily; 2010-2025 was a stable recovery phase, as similarity slightly rose and stabilized, aligning with key sociocultural time points. Based on evolution features, they fall into four groups: rapidly derogatory ("emo", "lying flat", "breaking down") shifting from neutral to strongly negative daily expressions; semantic generalization ("Versailles", "Buddhist-like", "being obsessed with") expanding from specific references to neutral daily expressions with weakened intensity; gradually neutralized ("inner conflict") evolving from a derogatory management term to a neutral personal mental description; semantically stable ("torment", "dilemma", "confusion") retaining steady core negative emotions with minimal fluctuations.

4.3.3. The diachronic semantic evolution trajectories of Chinese emotional words

The meanings of online popular emotional words shift rapidly in emotional polarity, semantic intensity, and pragmatic functions, their usage scenarios expanding from specific neutral domains to daily emotional expressions. In 1995, most such words had specific connotations (e.g., "emo" referring to a music style and "Versailles" a place name). After 2010, driven by youth subculture and social media, their semantics evolved fast (e.g., the generalization of "Buddhist-like" and "lying flat" became a mainstream social term), with new meanings fully solidified and low similarity retained. Traditional emotional words feature stable core semantics with only marginal fine-tuning and no fundamental changes—their core meanings stay unchanged, while their usage scenarios are extended or their focus shifts to psychological expression. "Inner conflict" is exceptional: it has

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expanded from an organizational management term to referring to individuals' mental self-consumption, its negative connotation weakened to neutral, with minimal overall data fluctuations.

4.3.4. The division and description of typical evolutionary word groups

The ten Chinese emotional words fall into four evolutionary patterns, with their temporal semantic shifts showing consistent categorical trends. The fast-derogatory group (emo, lying flat, breaking down) evolves from neutral professional/behavioral descriptions to strongly negative daily expressions, accelerated by social media. The generalized-attenuated group (Versailles, Buddhist-like, being obsessed with) expands reference from specific to neutral daily contexts, with weakened semantic intensity and broader applicability. The gradually neutralized group (only inner conflict) stems from a derogatory management term, its reference extended to personal mental friction and the derogatory connotation faded to neutral. The semantically stable group (torment, dilemma, confusion) keeps high similarity with minimal fluctuations for decades, retaining fixed core negative emotions and little impact from online culture.

4.4. Based on LLMs generation and evidence triangle mutual evidence attribution analysis

4.4.1. Attribution analysis framework and methods

In this framework, LLMs serve as heuristic hypothesis generators rather than final authorities, adopting a triangulation verification approach centered on "hypothesis-driven, evidence-supported, cyclic verification". Through human-machine collaboration, key hypotheses are generated and screened, then cross-verified by multiple evidence sources (news databases, statistical reports), excluding false associations via data and case verification to enhance attribution reliability. Hypotheses include internal linguistic and external social attributions, which interact to shape semantic evolution.

4.4.2. Internal language attributions of Chinese emotional words

Internal linguistic attribution is analyzed from word formation and syntactic environment. Word formation flexibility affects change degree and speed: loanwords, proper nouns, and some compound words ("emo", "Versailles", "lying flat") are prone to semantic reconstruction, while words with tight morpheme combinations ("torment", "dilemma") maintain stable core meanings. Syntactic environment adjustment promotes semantic evolution through three paths: syntactic function expansion (e.g., "lying flat" expanding usage scenarios), collocation relationship changes (e.g., "breaking down" collocation objects becoming abstract), and common sentence pattern influences (e.g., "emo" meaning changing with sentence pattern shifts).

4.4.3. Social external attribution of Chinese emotional words

Online dissemination and youth subculture are key external factors for Internet emotional words' semantic changes: after 2010, social media algorithmic dissemination accelerated the emotional transformation of words like "emo" and "Versailles". Economic and social changes (economic growth slowdown, intensified competition) drove "lying flat", "inner conflict" to evolve into expressions of life attitudes and psychological states. Cultural tradition stability ensures the continuity of traditional emotional words' core meanings ("torment", "dilemma", "confusion"),

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which express universal human emotions and are less affected by short-term trends, with minor usage adjustments to adapt to modern social needs.

4.4.4. Evaluation and reflection on the attribution ability of LLMs

LLMs' hypothesis that "internal linguistic laws and external social influences jointly drive semantic evolution" is fully verified by external data. Internet buzzwords' transformation conforms to linguistic laws and social phenomena (e.g., "emo" aligning with youth depression trends), while traditional words' evolution is consistent with dictionary adjustments and youth research data. The "LLM hypothesis - factual verification - internal-external cause matching" closed loop enhances conclusion reliability, providing a methodological reference for future interdisciplinary language change research.

5. Conclusion

This research explores 10 Chinese emotional words (1995-2025) to examine diachronic meaning changes and driving forces. Using LLM context embedding, spatial vector alignment, and quantitative-qualitative integration, it finds word meaning evolution features a gradual overall change and group differentiation (rapid internet word reconstruction, stable traditional word core, unique internal friction paths). Social media is a core external driver, with usage frequency affecting evolutionary stability. The verified, reliable method enriches digital-era language diachronic change theory.

When exploring the changing meanings of Chinese emotional words in this research, this research has four limitations with corresponding future adjustments: First, the 10-word sample lacks representativeness, with incomplete coverage of emotion types, intensities, and parts of speech. Future research should expand sample coverage and duration to refine the semantic evolution picture. Second, the corpus is single-type and unevenly sourced; a comprehensive corpus and "vocabulary-context-user" 3D annotation system should be built for standardization. Third, quantitative indicators for meaning change are singular, with unclear driving factor weights and interactions; research methods need innovation.

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