Do LLMs Understand Wine Descriptors Across Cultures? A Benchmark for Cultural Adaptions of Wine Reviews

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Abstract

Leveraging remarkable advancements in Large Language Models (LLMs), we are now poised to tackle increasingly complex challenges requiring deep comprehension of multifaceted domains and contexts. A specific application scenario is wine reviews adaptation. Wine reviews usually describe a wine's appearance, aroma, and flavor to help consumers appreciate its characteristics. However, the adaptation of wine reviews transcends mere translation; it requires consideration of regional preferences, flavor descriptors, and cultural nuances that shape wine perception. We introduces the first-ever task involving the translation and cultural adaptation of wine reviews between Chinese and English. In a case study on cross-cultural wine review adaptation, we compile a dataset of 8k Chinese and 16k Western professional wine reviews. We evaluated various methods, including LLMs and traditional machine translation techniques, using both automatic and human metrics. For human assessments, we introduce three novel cultural-related metrics—Cultural Proximity, Cultural Neutrality, and Cultural Genuineness—to gauge the success of different approaches in achieving authentic cross-cultural adaptation. Our analysis shows that current models struggle to capture cultural nuances, especially in translating wine descriptions across different cultures. This highlights the challenges and limitations of translation models in handling cultural content.

1 Introduction

Wine reviews serve as valuable guides for consumers, offering detailed insights into the characteristics of each bottle. For casual drinkers and connoisseurs alike, these reviews act as a compass, helping them navigate the vast selection of wines available. However, due to cultural influences and geographical distinctions, beverage consumption patterns and individual preferences vary significantly across regions (Rodrigues and Parr, 2019),

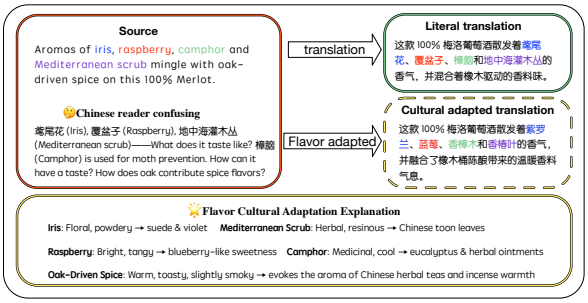


Figure 1: An example of Literal vs. Cultural Adapted Translation, Enhancing Readability in Wine Descriptions, highlighting how certain descriptors and flavor terms require adaptation for better comprehension by culturally unfamiliar readers.

not to mention reviews. These variations extend beyond mere differences in taste and are deeply rooted in the cultural, social, and environmental contexts of each region. Consequently, consumer preferences for certain beverages, including wine, can differ greatly, often rendering generalized reviews less relevant or applicable across diverse audiences. Professional reviews play a greater role than user reviews in promoting consumer purchases (Chiou et al., 2014). For Chinese wine consumers, professional wine reviews in Chinese are scarce, and most available reviews require a paid subscription. Similarly, Western consumers face challenges finding professional reviews of Chinese wines. This paper aims to bridge these gaps by providing a comprehensive, culturally inclusive dataset of bilingual wine reviews, supporting a more globally relevant perspective on wine preferences.

Recognizing and adapting to cultural differences in language use is both essential and challenging (Hershcovich et al., 2022), especially for subjective comments. Translations of reviews using current neural machine translation systems may overlook culture-specific expressions or result in mistranslations due to insufficient grounding in physical and cultural contexts. For instance, in Figure 1, 'rasp-

berry', a common European flavor descriptor, is rare in China ('覆盆子'), making its taste unfamiliar to Chinese consumers. The flavor of raspberry is puzzling to Chinese consumers, and requires additional explanation or finding a fruit with a similar flavor. 'Blueberry,' which has a similar flavor profile (Jin et al., 2022), is more popular and better understood by Chinese consumers. All the outputs of this example are shown in Appendix H.

While wine reviews traditionally rely on human expertise to capture nuanced sensory experiences, providing detailed descriptions of a wine's appearance, aroma, and flavor. However, these reviews are deeply influenced by cultural norms, linguistic styles, and regional preferences, making their translation across languages a complex task. Recent advancements in LLMs offer new opportunities to analyze and generate detailed reviews (Wu et al., 2025). By leveraging their ability to parse intricate descriptions and contextual nuances, LLMs provide an opportunity to analyze how cultural nuances and stylistic elements are preserved or transformed during translation.

In this work, we introduce the task of adapting wine reviews across languages and cultures. Beyond direct translation, this requires adaptation concerning content and style. We focus on Chinese and English wine reviews, automatically pairing reviews for the same wine from the same vintage from two monolingual corpora. As there are many reviews in English for the same wine, we also explore the inner difference in reviews from people of the same culture. We evaluate our methodology with human evaluation and automatic evaluations on the dataset we construct. Our contributions are as follow:

1. We introduce the task of cross-cultural wine reviews translation and build a bidirectional Chinese-English dataset with multiple references for it: CulturalWR.

2. We experiment with various sequence-to-sequence approaches to adapt the reviews, including machine translation models and multilingual LLMs.

3. We evaluate and analyze the difference between Chinese and English-speaking cultures and how they describe wine characteristics.

2 Related Work

Computational analysis of wine reviews. Recent advancements in wine informatics have leveraged computational techniques to analyze expert wine reviews. The Computational Wine Wheel 2.0 facilitates machine learning-based wine attribute analysis (Chen et al., 2016). In addition, studies applying SVMs to wine reviews have demonstrated the impact of different review sources on high-quality wine prediction (Tian et al., 2022). Machine learning and text mining techniques have also been utilized to discover predictive patterns in wine descriptions, challenging the notion that flavor descriptions are purely subjective (Lefever et al., 2018). These studies provide a foundation for computational analysis of wine reviews, yet they primarily focus on prediction tasks rather than cross-cultural aspects of wine appreciation.

Cross-cultural analysis of flavors. Flavor perception varies across cultures, as shown in studies analyzing beer pairing preferences in Latin America (Arellano-Covarrubias et al., 2019) and color-flavor associations in snack packaging across China, Colombia, and the UK (Velasco et al., 2014). Research on cheddar cheese flavor lexicons across different countries (Drake et al., 2005) further highlights cultural influences on taste perception. These findings underscore the need for culturally adaptive approaches in wine description and translation.

Cultural adaptation. As culture and language are intertwined and inseparabled, there is a rising demand to equip machine translation systems with greater cultural awareness (Nitta, 1986; Ostler, 1999; Hershcovich et al., 2022). However, it is costly and time-consuming to collect culturally sensitive data and perform a human-centered evaluation (Liebling et al., 2022). A recent study showed that LLMs are adept at adapting cooking recipes across cultures, using a comparable and a parallel corpus (Cao et al., 2024). Our work focuses on the translation of non-parallel subjective reviews, an area that remains underexplored.

3 The CulturalWR dataset

We present CulturalWR, a dataset of paired professional wine reviews. Each pair consists of one Chinese review by Chinese wine critics and, when available, an English review by the same authors, alongside multiple English reviews authored by

Western wine critics for the same wine, identified by the wine name and its corresponding vintage.

3.1 Data Collection

We collect the English wine reviews from several professional wine review websites, including Robert Parker's Wine Advocate[1], Wine Spectator[2], James Suckling[3], Wine Spectator[4] and some other professional wine review websites. Chinese wine reviews are primarily written by two prominent reviewers, AlexandreMa[5], ShenHao[6], who often publish bilingual wine reviews and China Wine Information Network[7].

3.2 Wine Matching Rules

Wine names are usually derived from regions or grape varieties, labeled by these features or a unique name. We observed that Chinese reviewers often skip mentioning the grape variety and region, opting for simpler names. To match reviews to specific wines, we use a string matching algorithm that includes converting non-English characters from languages like Spanish and French to English. This addresses variations in spelling, such as "Château Nénin" versus "Chateau Nenin". Exact matches are assumed to indicate the same wine; partial matches undergo manual verification.[8] After confirming the names and vintage years match, we finalize the reviews for each specific wine.

3.3 Data Filtering Rules

To focus on red wines and adapt reviews culturally, we applied three filtering rules: excluding Non-Vintage (N.V.) wines due to inconsistent tasting notes over time, separating white and rosé wines into distinct datasets for independent testing, and filtering out reviews under 30 words in English or 30 characters in Chinese for lack of detail.

3.4 Dataset Overview

We collect approximately 20k Chinese wine reviews covering nearly 20k wines, along with 150,000 English wine reviews spanning over 30k wines. These reviews encompass a variety of wine types, including red, white, rosé, and champagne. After filtering, we retain around 10k Chinese reviews focused on red wines. Through matching, the dataset is refined to include 4.5k wines, comprising about 4.5k Chinese reviews and 16k English reviews. 3,227 Chinese reviews have their matched English reviews written by the same author. Data statistics are shown in Table 1.

	Number	Mean #Tokens
CA Chinese Reviews	4776	67.57
CA English Reviews	3227	74.25
Transl. Chinese Reviews	60	60.2
WA English Reviews	16746	58.16

Table 1: Statistics of reviews. CA refers to Chinese wine critics and WA to Western ones. We count tokens with `jieba` text segmentation for Chinese and whitespace tokenization for English.

Attributes. Besides the basic reviews and their corresponding rating for each wine, we sourced wine data from different sources, we reorganize the basic attributes of all these wines, which includes the geographical location of the winery, the composition of the grape varietals, the vintage, the alcohol content and the price. To ensure privacy, we anonymized the obtained data, and no personally identifiable information is included in the attributes. It's shown in F.

4 Analysis of Chinese Reviews and Western Reviews

We frame three insights gained in this section, that not only reveal that professional wine reviews are confusing to ordinary consumers, but also show the cultural similarities and differences between professional reviews. These highlight the necessity for cultural adaptations of wine reviews.

Insight #1: Wine reviews are not always intuitive to consumers. While most reviews are relatively easy to understand, some flavor descriptors—such as 'Leather', 'Tar' and 'Cat's Pee'—are confusing or unappealing to those unfamiliar with wine terminology. However, they are widely used by Western reviewers to describe red wines. This gap between expert notes and reader intuition can make reviews feel inaccessible.

Insight #2: High Semantic Similarity Between Chinese and Western Wine Critics' Reviews.

[1] https://www.robertparker.com/
[2] https://www.winespectator.com/
[3] https://www.jamessuckling.com/
[4] https://www.winespectator.com/
[5] https://www.alexandrema.com
[6] http://www.leparadisduvin.com
[7] www.winesinfo.com
[8] Particularly in the Bordeaux region, wines use the winery's name for the Grand Vin (first wine) and unique names for second and third wines, with "blanc" added for white wines.

We extracted detailed flavor descriptors from wine reviews and used Jaccard Similarity to analyze cultural differences. Leveraging the Wine Aroma Wheel from Aromaster[9], we measured both inner and outer similarity across three hierarchical layers: Aroma Families (broad categories such as fruits, flowers, and spices), Aroma Subfamilies (more specific groups like citrus fruits, red berries, and dried herbs), and Exact Aromas (precise descriptors such as lemon, raspberry, or thyme).

Although the Wine Aroma Wheel includes 88 commonly used wine aromas, we identified over 300 distinct precise descriptors in the reviews. For Exact Aromas, both inner and outer similarities[10] are below 0.1, with outer similarity significantly lower than inner similarity. At the Aroma Subfamily level, outer similarity increases to 0.16, catching up with inner similarity. For Aroma Families, outer similarity exceeds 0.4, indicating some degree of convergence. However, overall Jaccard similarity remains relatively low. We attribute this to differences in reviewing styles: some reviewers describe only dominant flavors in complex red wines, while others list all detectable aromas.

Additionally, we evaluated cosine similarity and BERTScore (Zhang* et al., 2020) for cross-group and within-group comparisons. Both metrics consistently exceed 0.8, suggesting a high degree of semantic similarity between Chinese and Western wine reviews.

Insight #3: Chinese Reviews have a significantly distinct boundary compared to the overall distribution of Western Reviews. Different from Insight #2, we do dimensionality reduction using PCA on the embeddings[11], as shown in Figure 2, the two sets of embeddings exhibit a clear boundary in the lower-dimensional space. This suggests that the two groups of comments have substantial differences in their global structure and overall semantic distribution. PCA amplifies these differences, uncovering separation that is not evident through BERTScore's local similarity focus. This also shows the importance of cultural adaptations.

[9] https://aromaster.com/

[10] "Outer" refers to comparisons between Chinese and Western reviews, while "Inner" refers to comparisons within Western reviews.

[11] We obtain embeddings from the last hidden layer's hidden states from ChatGLM

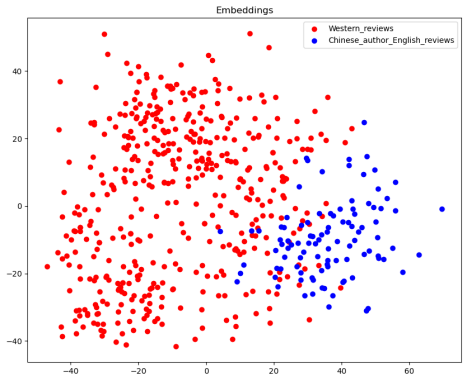


Figure 2: PCA-reduced embeddings: Red dots show Western reviews, and blue dots show English reviews by Chinese authors

5 Cross Cultural Wine Reviews Adaptation Task

We propose cross-cultural wine review adaptation, extending machine translation by requiring both accuracy and deliberate semantic divergence to address cultural differences.

Evaluating cultural adaptation is challenging, as it must balance meaning preservation with genuine cross-cultural differences. In wine review adaptation, we even need to adapt the flavor descriptors. As common in text generation tasks, we first adopt reference-based automatic evaluation metrics. Moreover, considering reference-based metrics are often unreliable for subjective tasks, we also conduct human evaluations.

5.1 Automatic Evaluation

We use four metrics to assess the similarity between the generated and reference reviews. We use two lexical-based metric: BLEU (Papineni et al., 2002), a precision metric based on token n-gram which emphasizes precision and commonly used in machine translation evaluation and METEOR (Banerjee and Lavie, 2005), which combines precision and recall while incorporating linguistic features such as stemming and synonymy to provide a more comprehensive evaluation; one contextual-embedding based metric: BERTScore (Zhang* et al., 2020), based on cosine similarity of contextualized token embeddings and capture deep semantic matching; one hybrid-based metric: Beer (Stanojević and Sima'an, 2014), based on multi-feature fusion regression indicator, which combines syntactic and semantic features to automatically evaluate translation quality through regression model learning.

5.2 Human Evaluation

While automatic metrics provide quantifiable results, they rely on fixed reference sets, which may lack cultural relevance. To address this, we introduce seven human evaluation criteria applied to the test set.

(1) **Grammar**: The generated reviews are grammatically correct and fluent; (2) **Faithfulness of Information**: The content accurately reflects the original input without introducing false or misleading information; (3) **Faithfulness of Style**: The output preserves the original tone, register, and formality without altering the intended voice; (4) **Overall quality**: The reviews are coherent, contextually appropriate, and align with the intended tone and style; (5) **Cultural proximity**: The generated reviews use familiar terms and expressions that resonate with the target culture. For example black currant was replaced by Chuanbei loquat paste, cough syrup and hawthorn cake in Chinese localised aroma wheel (Jin et al., 2022); (6) **Cultural Neutrality**: Maintains neutrality to avoid provoking negative perceptions or reactions from the target culture consumers. For example, 'earthy' can be a positive descriptor for wine in the West. However, when translated into Chinese, '土味' often implies a dirty or unrefined flavor. A more elegant term like '泥土气息' (aroma of soil) is often preferred; (7) **Cultural Genuineness**: Preserves the quality of the original descriptor without altering its meaning, ensuring authenticity. For example clove, violet and saffron have no suitable local descriptors with similar olfactory characteristics.

Our evaluation was done by three people fluent in both Chinese and English, including two master students and a professor. Before the evaluation process, we performed preliminary testing on 40 samples and used Pearson correlation to calculate their understanding of different metrics which proved these metrics are easy for people to evaluate.

6 Experiment

To comprehensively assess the efficacy of LLM translations in understanding wine and flavors, we compare various prompting strategies on tuning-free LLMs, alongside evaluations of an open-source Machine Translation model.

6.1 Experimental Setup

Prompting LLMs. Based on the exceptional performance of multilingual LLMs in zero-shot translation. We explore their ability on translating wine reviews and flavor adaptation.

We compare the performance of five diverse, state-of-the-art LLMs on this task. We test Llama-3.1-8B-Instruct (AI@Meta, 2024), Mistral-7B-Instruct-v0.3 (Jiang et al., 2023),Phi-3.5-mini-instruct (Abdin et al., 2024), and ChatGPT-4o (OpenAI et al., 2024) and two use more Chinese training data models: Qwen2.5-7B-Instruct (Yang et al., 2024), GLM4-9b (GLM et al., 2024). We used Cultural Prompt in Table 9.

Multilingual machine translation model: We use the state-of-the-art NLLB-200-3.3B model (Team et al., 2022) for accurate, context-aware multilingual translation in our experiments.

7 Results and Analysis

Our analysis includes five parts: 1)automatic evaluation between different models; 2) fine-grained human evaluation on a subset of Chinese-English translation bidirectional; 3) Correlation of automatic metrics with humans; 4) Different prompting strategy evaluation comparison; 5) Quantitative analysis for some specific concepts

7.1 Overall Automatic Evaluation

Models	BLEU	METEOR	B-Sc	BEER	#Tok
Chinese → English					
ChatGLM4	**18.7**	45.7	86.7	51.5	65.8
Phi	10.9	40.6	90.0	47.5	75.6
Qwen2.5	15.6	**46.3**	**91.2**	**52.7**	69.2
Mistral	5.2	36.4	87.9	34.1	61.8
Llama3.1	11.4	35.2	88.0	44.3	54.0
NLLB	12.0	36.8	88.7	48.1	64.8
English → Chinese					
ChatGLM4	8.9	**31.9**	86.6	26.5	130.5
Phi	4.8	25.8	89.8	22.5	94.7
Qwen2.5	**12.3**	36.4	**90.6**	**29.3**	85.7
Mistral	2.0	20.1	89.3	17.0	56.1
Llama3.1	9.9	**31.9**	87.3	28.1	89.5
NLLB	3.8	18.3	87.6	21.4	96.8

Table 2: Automated evaluation results on the test sets using reference-based metrics: BLEU, METEOR, B-Sc(BERTScore) and BEER. Higher scores indicate better performance on all metrics.

For Chinese-to-English translation, ChatGLM4 achieved the highest BLEU score, suggesting strong lexical matching, while Qwen2.5 excelled in BERTScore and BEER, indicating superior

semantic alignment with human-written translations. For English-to-Chinese translation, Mistral led in BLEU, while Llama3.1 scored highest in METEOR, and Qwen2.5 again outperformed in BERTScore and BEER, reinforcing its strength in preserving meaning. Notably, ChatGLM4 struggled with BLEU and METEOR in this direction but maintained competitive BERTScore values, suggesting it prioritizes semantic coherence over strict lexical overlap. Additionally, the NMT system NLLB still remains highly competitive. Overall, Qwen2.5 consistently demonstrated high semantic quality across both directions, while other models exhibited strengths in specific metrics, reflecting differing optimization objectives. These results highlight the inherent trade-offs between fluency, lexical fidelity, and semantic preservation across models. More importantly, they underscore that reference translations are not the sole "correct" adaptations, as translation quality is inherently subjective. This reinforces the need for a nuanced evaluation framework that accounts for cultural context, linguistic variation, and domain-specific preferences to better capture real-world translation quality.

7.2 Human Evaluation

Models	F-I	F-S	Gr	O-Q	C-P	C-G	C-N
Chinese → English							
ChatGLM4	5.6	4.8	5.3	5.0	6.8	**6.4**	6.2
Phi	4.8	5.4	6.0	4.8	6.9	6.3	**6.4**
Qwen2.5	**5.8**	**6.0**	5.8	**5.5**	6.8	6.3	**6.4**
Mistral	4.8	5.7	6.0	4.8	**7.0**	**6.4**	6.3
Llama3.1	5.3	5.6	**6.2**	5.3	**7.0**	6.2	6.3
Human	5.5	5.3	5.5	5.3	6.6	6.3	6.2
English → Chinese							
ChatGLM4	5.5	5.5	4.2	4.7	5.6	5.5	5.3
Phi	4.1	4.5	3.6	3.7	5.6	4.4	5.3
Qwen2.5	**5.7**	**5.9**	**5.5**	**5.6**	**6.0**	5.5	**5.8**
Mistral	3.8	4.4	2.8	3.1	4.8	4.6	4.7
Llama3.1	4.5	5.0	4.4	4.6	5.9	4.8	5.7
Human	5.1	5.8	5.2	5.0	5.8	**5.7**	**5.8**

Table 3: Human evaluation results on the selected test sets: average for each method and metric, ranging from 1 to 7. F-I, F-S, Gr, O-Q, C-P, C-G and C-N representing Faithful of Information, Faithful of Style, Grammar, Overall Quality, Cultural Proximity, Cultural Genuineness and Cultural Neutrality respectively

Table 3 presents the results of human evaluation across multiple dimensions. Notably, NLLB was excluded from human evaluation due to its lack of cultural adaptation capabilities.

For English-to-Chinese translation, Qwen2.5 leads across most metrics, even surpassing human translations in faithfulness, grammar, and overall quality. Human translations score highest in Cultural Genuineness, reflecting their ability to preserve nuanced expressions. Llama3.1 also remains competitive, balancing fluency and cultural adaptation.

For Chinese-to-English translation, Qwen2.5 again ranks highest in faithfulness and overall quality, while Mistral outperforms even human translations in Cultural Proximity and Genuineness, suggesting a stronger emphasis on natural, idiomatic English.

These results highlight trade-offs between literal accuracy and cultural adaptation. While human translations excel in cultural authenticity, LLMs like Qwen2.5 demonstrate strong faithfulness, and Mistral prioritizes fluency in the target language. This underscores the importance of context-aware evaluation that considers both linguistic accuracy and cultural nuances.

Methods	F-I	F-S	Gr	O-Q	C-P	C-G	C-N
Chinese → English							
Human-Eval	5.36	5.58	5.91	5.19	6.86	6.31	6.36
GPT4o-Eval	5.79	5.24	6.47	5.77	5.23	5.4	6.44
English → Chinese							
Human-Eval	4.57	5.02	4.44	4.13	5.25	5.12	5.0
GPT4o-Eval	5.76	5.36	6.2	5.71	5.39	5.58	6.43

Table 4: GPT-4o v.s. Human in Human evaluation metrics(Average over All Human Test Cases)

GPT-4o and Human Evaluation Diverge. Table 4 shows the results evaluated by both GPT-4o and human annotators. Specifically, we use all the human evaluation test cases for GPT evaluation. The results show that GPT and Human evaluation scores are not strongly correlated and GPT has a higher tolerance than humans especially for English → Chinese direction. This discrepancy suggests that GPT-4o may have a different interpretation of translation quality compared to human evaluators. This discrepancy is particularly evident in culturally relevant metrics. The prompts we used are shown in C.

7.3 Correlation of automatic metrics with humans

To evaluate the reliability of automatic metrics for wine review adaptations, we analyze their correlation with human evaluations across seven metrics using Kendall correlation, the WMT22 meta-evaluation standard (Freitag et al., 2022).

As illustrated in Table 5, the correlation between

	BLEU	METEOR	B-Sc	BEER
Chinese → English				
F-I	0.2536*	0.1892	0.3000*	0.2442*
F-S	0.0053	0.0075	0.0204	0.0113
Gr	-0.0296	-0.0096	0.0033	-0.0478
O-Q	0.2191*	0.1847*	0.2061*	0.2015*
C-P	-0.070	-0.0177	-0.0540	-0.0961
C-G	0.1131	0.0625	0.0621	0.1131
C-N	-0.1166	-0.0841	-0.0166	-0.0876
English → Chinese				
F-I	0.4079*	0.2788*	0.4080*	0.2946*
F-S	0.3723*	0.3560	0.3769*	0.3904*
Gr	0.2819*	0.2788*	0.3530*	0.2946*
O-Q	0.3526*	0.3123*	0.3742*	0.3557*
C-P	0.1408	0.1524	0.2609*	0.1553
C-G	0.3134*	0.3170*	0.3942*	0.3170*
C-N	0.1334	0.1357	0.2389*	0.1516

Table 5: Kendall correlation of human evaluation results with automatic metrics. Statistically significant correlations are marked with *, with a confidence level of $\alpha = 0.05$ before adjusting for multiple comparisons using the Bonferroni correction

human evaluation results and automatic metrics varies across different translation directions and evaluation criteria. For Chinese → English, F-I (Faithful of Information) and O-Q (Overall Quality) exhibit the strongest correlations, particularly with BLEU, B-Sc, and BEER, suggesting that these metrics align well with human judgments in assessing fluency and overall translation quality. On the other hand, for English-Chinese, the correlations are generally stronger across all metrics. Notably, F-I, F-S (Faithful of Style), and O-Q display significant correlations with multiple metrics, particularly B-Sc and BEER, indicating that these metrics are relatively more reliable for evaluating fluency and intelligibility in English-to-Chinese translations.

C-G (Cultural Genuineness) also achieves strong correlations indicating that automatic metrics can reliably assess translation accuracy. However, this does not necessarily reflect the cultural adaptability of the translation. However, C-N(Cultural Neutrality) and C-P(Cultural Proximity) remain weakly correlated, revealing that automatic metrics still fall short in capturing deeper cultural nuances, emphasizing the need for human evaluation. Notably, correlations for English→Chinese generally exhibit greater strength than Chinese→English. This discrepancy is likely due to most wine reviews being written from a predominantly Western reviewer's perspective.

Human Evaluation							
Methods	**F-I**	**F-S**	**Gr**	**O-Q**	**C-P**	**C-G**	**C-N**
Direct Translation	6.38	5.94	5.56	5.69	4.38	6.31	5.81
Cultural Prompt	6.25	6.12	5.88	5.94	4.5	6.19	5.94
Detailed Cultural Prompt	5.75	5.94	5.75	5.56	4.88	5.69	5.69
Self-Explanation	4.94	5.75	5.88	5.5	5.75	4.56	6.62

Automatic Evaluation				
Methods	**BLEU**	**METEOR**	**B-Sc**	**BEER**
Direct Translation	16.5	41.6	91.4	28.3
Cultural Prompt	15.9	41.0	91.3	28.3
Detailed Cultural Prompt	14.4	38.6	91.0	27.6
Self-Explanation	13.7	37.0	90.9	27.6

Table 6: Evaluation of different strategies by GPT4o on English-Chinese translations.

7.4 Prompting Strategy Evaluation

With LLM-based machine translation advancing, integrating free-form external knowledge offers new opportunities to enhance translation quality. We compare different prompting strategies on ChatGPT for English-to-Chinese translation, including Direct Translation, Cultural Prompt, Detailed Cultural Prompt, and Self-Explanation. Table 9 lists the specific prompts.

As is shown in Table 6, Direct Translation is the best-performing method in Faithful of Information and automatic metrics. Cultural Prompting improves cultural accuracy slightly but does not significantly enhance overall translation quality. Self-Explanation has the worst faithful scores but is rated the best in Cultural Neutrality, making it a trade-off strategy for culturally rich contexts. This trade-off suggests that translation strategies need to balance faith, accuracy, and cultural adaptability, depending on the intended use case.

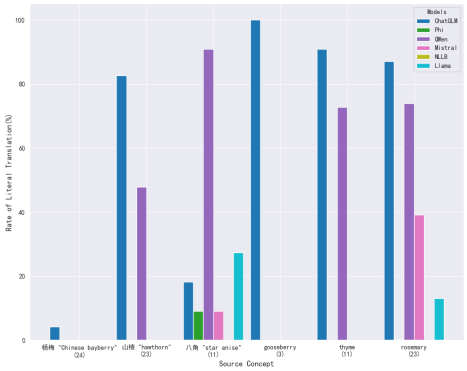
7.5 Quantitative analysis

Cross-lingual translation of culturally specific concepts is challenging, as it requires balancing linguistic accuracy with cultural adaptation. Many models tend to rely on literal translation, which may not always convey the intended meaning naturally. To examine this, we evaluate each model's literal translation rate for culturally embedded flavor descriptors from the CulturalWR test set. For instance, in English-to-Chinese translation, 'thyme' is considered an English-specific concept. We count occurrences of related terms such as 'gooseberry', 'thyme', and 'rosemary' in English wine reviews (c_{source}) and record how often they are directly translated in the corresponding Chinese reviews (c_{target}) from model predictions. The literal translation rate is then calculated as $\frac{c_{target}}{c_{source}}$. To further assess translation quality, we conduct a

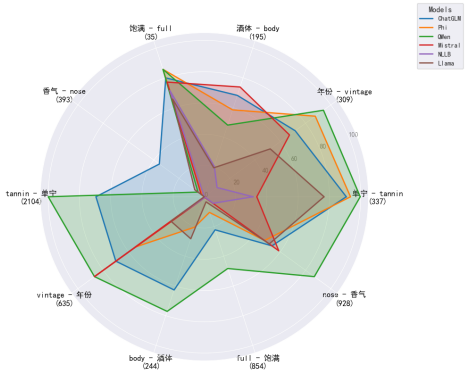
bidirectional test on the five most common wine-related terms. This ensures that models not only preserve culturally specific terms when translating in one direction but also effectively map key wine descriptors between languages. Comparing accuracy across models provides insights into their ability to maintain semantic fidelity, crucial for expert-level wine translations.

As shown in Figure 3a,we analyze six culturally relevant concepts, three common in Chinese culture and three in Western culture. Results show significant differences in literal translation rates across models ChatGLM and Qwen, with a stronger emphasis on Chinese-language data, exhibit higher literal translation rates, prioritizing structural fidelity over adaptation. For Western cultural concepts, Llama and Mistral show some degree of accurate literal translation, though performance varies. Notably, no model directly translates 'waxberry', likely due to its regional specificity and the absence of a widely recognized equivalent in Western languages. NLLB struggles with all six concepts, highlighting potential NMT limitations. Furthermore, while Llama and Mistral do not achieve the highest literal translation rates, they demonstrate a tendency to adapt culturally specific terms rather than translate them directly. For example, they often map 'raspberry' to other red berries such as 'blueberry' and 'blackberry' and replace 'thyme' with similar spices like 'bay leaves' and 'cinnamon'. These adaptations align with the categorization in the Wine Aroma Wheel, as both the substituted berries and spices belong to the same Aroma Subfamilies. These findings are consistent with Table 3, where ChatGLM and Qwen score higher in Faithfulness of Information, while Llama and Mistral perform better in Cultural Proximity.

We further assess how well models handle wine terminology, which often has industry-specific meanings distinct from general usage. As shown in Figure 3b, ChatGLM and Qwen perform well in translating these terms, while Phi also ranks highly, even leading for 'full'. However, challenges arise with terms such as 'nose', which refers to a wine's aroma in professional contexts. The phrase "on the nose" describes a wine's bouquet, yet most models translate 'nose' directly, failing to capture its specialized meaning. This highlights the challenge of translating wine-specific terms beyond their literal meanings and underscores the importance of integrating domain knowledge into machine translation models.



(a) Analysis of the translation of specific concepts by the different models on the test data.



(b) Analysis of the translation of specific terminology by the different models on the test data.

Figure 3: Comparison of translation analysis: specific concepts vs. specific terminology. In brackets, we show the number of occurrences of each concept.

8 Conclusion

In this work, we studied cross-cultural adaptation of wine reviews, introducing CulturalWR, a dataset of paired Chinese and English reviews, and evaluating LLM-based adaptation methods. Our results show that LLMs can consider cultural nuances but face challenges in maintaining detail and consistency in flavor descriptions. We also assessed adapted flavor similarities to gauge LLMs' understanding of wine descriptors. Beyond wine reviews, our findings have broader implications for cross-cultural communication in the wine industry, aiding wineries and retailers in tailoring descriptions to international audiences. This could enhance global wine marketing while preserving cultural authenticity. Moreover, our work highlights AI's potential in gastronomy, paving the way for research into AI-assisted flavor profiling and food pairing. Future work includes refining adaptation models for coherence, integrating multimodal data, and using user feedback to enhance AI-generated adaptations, bridging cultural gaps in wine appreciation.

9 Limitation

Cultural adaptation in wine reviews has great potential to aid consumer decisions and promote wines globally. However, several challenges remain. A key limitation is the dataset size and diversity. Our study includes fewer than 5,000 Chinese reviews, primarily from three professional critics, raising concerns about representativeness. Additionally, while our dataset contains reviews in multiple languages (German, Portuguese, French, Dutch, Italian, and Spanish), we focused solely on Chinese and English due to resource constraints. Expanding multilingual analysis could offer further insights. Another constraint lies in evaluation prompts. Our analysis relies on four prompts, which may not fully capture how models handle cultural adaptation. Broader prompt variations and real-world user inputs could improve evaluation robustness. Moreover, our quality assessment is based on the Wine Aroma Wheel and prior sensory adaptation research (Jin et al., 2022), but it lacks independent verification of adaptation accuracy. Future work could incorporate human or expert evaluations for a more comprehensive assessment. Finally, wine reviews are inherently subjective, influenced by personal preferences and sensory perceptions. While we strive to minimize bias, eliminating subjectivity entirely remains challenging. Addressing this may require larger, more diverse datasets and structured sensory evaluation frameworks in future research.

Ethical Considerations

This study relies on wine ratings and tasting notes sourced from professional websites, which are used strictly for non-commercial academic research. Due to the proprietary nature of the data, we do not publicly release or redistribute any portion of it. Our use falls within the permitted scope of personal, non-commercial informational use, as outlined in the platform's Terms of Use, and all references are properly attributed. No automated data extraction or systematic collection was conducted, ensuring compliance with intellectual property and fair use policies. Additionally, all human evaluators involved in this research are co-authors of the paper and participated voluntarily without financial compensation.

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A French and Spanish Character Conversion Table

This section shows the Character Conversion Table we have used to convert some characters, shown in Table 7.

B Whole dataset of Other Languages

It's the all the data we have collected, besides Chinese and English, we also collected some reviews written in German, Portuguese, French, Dutch, Italian and Spanish.

Original	Converted	Original	Converted
à	a	â	a
ä	a	é	e
è	e	ê	e
ë	e	î	i
ï	i	ô	o
ö	o	ù	u
û	u	ü	u
ç	c	ÿ	y
æ	ae	œ	oe
À	A	Â	A
Ä	A	É	E
È	E	Ê	E
Ë	E	Î	I
Ï	I	Ô	O
Ö	O	Ù	U
Û	U	Ü	U
Ç	C	Ÿ	Y
á	a	í	i
ó	o	ú	u
ñ	n	Á	A
Í	I	Ó	O
Ú	U	Ñ	N

Table 7: French and Spanish Character Mapping to English

	Numbers	Mean Tokens
CA Chinese Reviews	4776	67.57
CA English Reviews	3227	74.25
WA English Reviews	16746	58.16
WA German Reviews	3341	50.73
WA Portuguese Reviews	161	82.15
WA French Reviews	480	135.63
WA Italian Reviews	40	44.35
WA Spanish Reviews	10	114.8

Table 8: Statistics of reviews. We count tokens with jieba text segmentation for Chinese and whitespace tokenization for other languages.

C Prompt Used for Evaluation

Table 9 shows different prompt strategies we used for Prompting Strategy Evaluation.

Here shows the prompt we used for GPT evaluation:

```
As a Western consumer, evaluate the
quality of wine review translation
from these dimensions, use seven-tier
scoring ranging from 1-7 : 7 means
Excellent, 6 means Very Good, 5
means Good, 4 means Fair, 3 means
Poor, 2 means Very Poor, 1 means
```

Strategy	Prompt
Direct Translation	Translate the following English wine reviews to Chinese: [Wine review]
Cultural Prompt	Translate the wine reviews in Chinese, adapted to an Chinese-speaking consumer: [Wine review]
Detailed Cultural Prompt	Translate the provided English wine review into Chinese, so that it fits within Chinese wine culture and to avoid using any terms that might have negative connotations for Chinese consumers: [Wine review]
Self-Explanation	User: Find flavor and aroma descriptions that are unfamiliar and uncomfortable for Chinese consumers: [Wine review] LLM: [Sentences] User: Translate the wine review in Chinese, and for the unfamiliar and uncomfortable flavor and aroma, replace it with a more familiar and comfortable description for Chinese consumers.

Table 9: Prompting strategy examples used for English → Chinese translation

```
Nonsense: Grammar,Faithfulness of
Information,Faithfulness of Style,
Overall quality,Cultural proximity
- The generated reviews use
familiar terms and expressions that
resonate with the target culture,
Cultural neutrality - Maintains
neutrality to avoid provoking
negative perceptions or reactions
from the target culture consumers,
Cultural Genuineness - Preserves
the quality of the original
descriptor without altering its
meaning, ensuring authenticity.
Original: {original}
Translation: {translation}
```

D Grading scale rule for human evaluation

Here shows the rule for the Seven-tier rating system:

1. Excellent (rating: 7 points)
   The translation is also highly matched in context and culture.

2. Very good (rating: 6 points)
   There may be slight (1-2) inaccuracy of vocabulary or inadequate reflection of some details, but it does not affect the overall understanding.

3. Good (rating: 5 points)
   There are individual mistranslations, but they will not seriously change the overall meaning.

4. Fair (score: 4 points)
   Mistranslations are obvious, which may cause some semantics to deviate from the original text.

5. Poor (score: 3 points)
   The overall translation quality is low and may mislead readers.

6. Very poor (score: 2 points)
   It is basically impossible to rely on the translation to understand the original text.

7. Nonsense (score: 1 point)
   The translation is completely incoherent semantically and unable to convey the information which the original review tries to convey.

E Human evaluation platform

Figure 4 shows a screenshot from our human evaluation platform, demonstrating the English to Chinese direction. Human need to evaluation the quality of Chinese translation

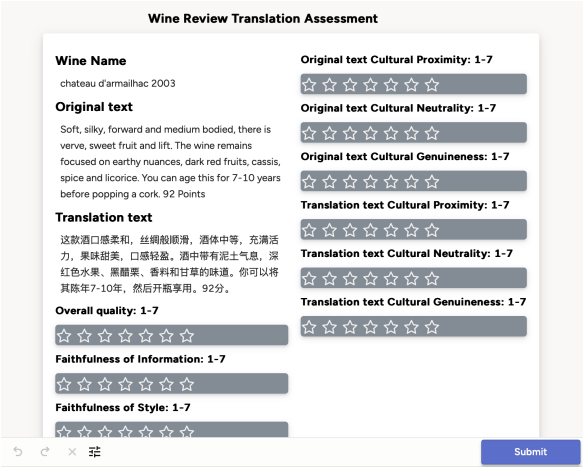


Figure 4: Screenshot from our human evaluation platform

F Attributes of Whole dataset

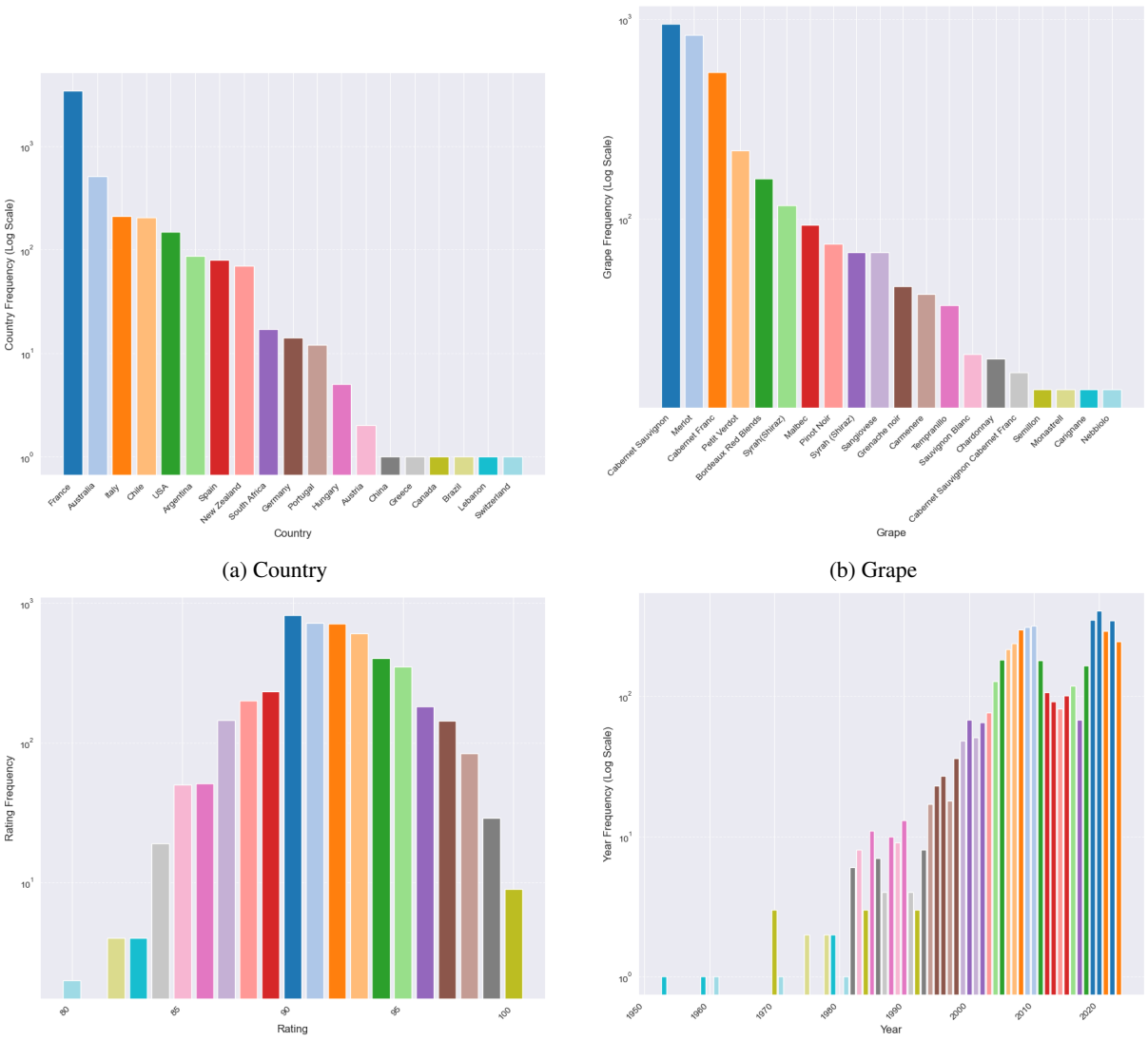
Figure 5 shows attributes counted in CulturalWR dataset.

G Experiment Settings

The experiment settings of different models included in our paper are as follows:

1. **NLLB** We use NLLB-200-3.3B[12] for our ex-

[12] https://huggingface.co/facebook/nllb-200-3.3B



(a) Country

(b) Grape

(c) Rating

(d) Year

Figure 5: Wine attributes.

periments. The beam is set as 4, and the length penalty is set as 1.0.

2. **Pretrained LLMs** We used LLMs including Llama-3.1-8B-Instruct [13], Mistral-7B-Instruct-v0.3 [14], Phi-3.5-mini-instruct[15], Qwen2.5-7B-Instruct[16], GLM4-9b[17]. The sampling is set as True, leading to a multinomial sampling searching method. All settings are the same across different models.

3. **ChatGPT** We used the latest version, GPT-4o-2024-11-20, through the ChatCompletion API provided by OpenAPI [18]. For the generation, we set the parameters as default, for which the temperature is 1, top_p is 1, and frequency_penalty as 0.

H Examples

In Table 10, we present a comparative analysis of multiple machine translation models applied to an English-to-Chinese translation example which is shown in Figure 1. Each row in the table represents the output of a different model, with the original English input provided for reference. To facilitate an in-depth evaluation, we systematically annotate

[13] https://huggingface.co/meta-llama/Llama-3.1-8B-Instruct

[14] https://huggingface.co/mistralai/Mistral-7B-Instruct-v0.3

[15] https://huggingface.co/microsoft/Phi-3.5-mini-instruct

[16] https://huggingface.co/Qwen/Qwen2.5-7B-Instruct

[17] https://huggingface.co/THUDM/glm-4-9b

[18] https://platform.openai.com/docs/guides/text-generation

Category	Content
Input (English)	Aromas of iris, raspberry, camphor and Mediterranean scrub mingle with oak-driven spice on this 100% Merlot.
ChatGLM4	这款酒散发着紫罗兰、树莓、樟脑和地中海灌木的香气，100%的梅洛。
Phi	这100%的梅鹿酒充满了茉莉花、覆盆子、茴香和地中海疏林的香气，与橡木风味相结合的精髓。
Qwen2.5	这款100%梅洛红酒散发出鸢尾花、覆盆子、薄荷和地中海灌木丛的香气，与橡木带来的香料味交织在一起。
Mistral	这是一款百分之一的梅洛酒，浓郁而舒服，携带了芙蓉花、莓果、樟木和植物的香气，以及橡木带来的香氛。
Llama	这款100%梅洛特红酒的香气中融合了百合花、草莓、樟脑和地中海灌木丛的气息，伴随着橡木驱动的香料。
NLLB	红虹，树，和地中海洗刷的香气与木驱动的香料混合在这个100%的梅罗特酒上。
ChatGPT	这款100%梅洛红酒散发出鸢尾花、覆盆子、樟脑和地中海灌木的香气，并与橡木带来的香料味交织在一起。

Table 10: Comparison of Translations from Different Models. Red text shows the wrong translation, teal text shows the correct literal translation, blue text shows the adapted translation and brown text shows unsure adapted translation.

various translation characteristics, including direct translations, adapted phrasings, and potential errors.

To facilitate evaluation, we use color coding to distinguish different translation characteristics: red indicates incorrect translations, teal represents accurate literal translations, blue highlights adapted translations that maintain meaning while improving fluency, and brown marks uncertain adaptations.

This comparison reveals variations in how different models interpret and translate key terms, particularly in handling domain-specific vocabulary such as "Merlot" and "Mediterranean scrub." Some models exhibit direct translation errors, while others apply adaptive strategies to enhance readability. By analyzing these differences, we can better understand the strengths and limitations of current machine translation systems.