JiraiBench: A Bilingual Benchmark for Evaluating Large Language Models' Detection of Human Self-Destructive Behavior Content in Jirai Community

Yunze Xiao^{1†}, Tingyu He^{2†}, Lionel Z. Wang^{3†§}, Yiming Ma³, Xingyu Song⁴, Xiaohang Xu⁴, Irene Li^{4‡}, Ka Chung Ng^{3‡}

¹Carnegie Mellon University ²University of Washington

³The Hong Kong Polytechnic University ⁴The University of Tokyo yunzex@andrew.cmu.edu, zhe-leo.wang@connect.polyu.hk, ireneli@ds.itc.u-tokyo.ac.jp, kc-boris.ng@polyu.edu.hk

Disclaimer: This paper describes human self-destructive content and potentially harmful behaviors including drug overdoese, eating disorders, and self-harming actions that may be disturbing to some readers.

Jirai Kei

1

2

3

8

9

10

11

12 13

14

15

16

17

18

19

20

21

"Jirai Kei" (in English: landmine style; in Chinese: 地雷系; in Japanese: じらいけい) refers to a transnational social media subculture that emerged in Japan during the early 2020s, gaining particular prominence during pandemic restrictions. The term literally translates to "landmine style", metaphorically representing psychological vulnerabilities that might "explode" when triggered. This community is characterized by individuals who publicly express various forms of psychological distress and self-destructive tendencies across social media platforms. Jirai communities exhibit distinctive communication patterns, including specialized terminology and coded language that conveys emotional vulnerability, particularly related to eating disorders, self-harm behaviors, and substance misuse. This phenomenon spans both Japanese and Chinese online spaces, creating interconnected networks where participants share experiences of psychological distress through culturally specific expressions.

Abstract

This paper introduces JiraiBench, the first bilingual benchmark for evaluating large language models' effectiveness in detecting self-destructive content across Chinese and Japanese social media communities. Focusing on the transnational "Jirai" (landmine) online subculture that encompasses multiple forms of self-destructive behaviors including drug overdose, eating disorders, and self-harm, we present a comprehensive evaluation framework incorporating both linguistic and cultural dimensions. Our dataset—comprising 10,419 Chinese posts and 5,000 Japanese posts—features multidimensional annotation along three behavioral categories with substantial inter-annotator agreement. Experimental evaluations across four state-of-the-art models reveal significant performance variations based on instructional language, with Japanese prompts unexpectedly outperforming Chinese prompts when processing Chinese content. This emergent cross-cultural transfer suggests that cultural proximity can sometimes outweigh linguistic similarity in detection tasks. Cross-lingual transfer experiments with fine-tuned models further demonstrate the potential for knowledge transfer between these language systems without explicit target language training. These findings highlight the need for culturally-informed approaches to multilingual content moderation and provide empirical evidence for the importance of cultural context in developing more effective detection systems for vulnerable online communities.

^{*&}lt;sup>†</sup>Equal Contribution §Project Leader [‡]Corresponding Authors

1 Introduction

Human self-destructive behaviors constitute a profound public health challenge (Baumeister & Scher, 1988). These behaviors manifest as deliberate acts of self-harm that can range from subtle to severe, including eating disorders (ED) characterized by extreme dietary restriction and purging, self-harm (SH) by cutting or burning, and drug overdose (OD) at levels that risk permanent harm or death. What makes these behaviors particularly concerning is their tendency to operate beneath the surface of conventional detection systems, often interwoven with complex mental health conditions such as depression, anxiety, post-traumatic stress disorder, or personality disorders (Van der Kolk et al., 1991; Firestone & Seiden, 1990). The digital era has further complicated this landscape, as online communities have emerged that sometimes normalize, reinforce, or provide methods for self-destructive behaviors, creating new challenges for intervention and prevention efforts.

Previous research efforts in detecting self-destructive behaviors online have made notable contributions but remain limited in scope and applicability. Most studies have focused narrowly on individual categories of concerning behaviors, examining eating disorders (ED) (Wang et al., 2017a; Moessner et al., 2018; Chancellor et al., 2016a), self-harm (SH) (Wang et al., 2017b; Un Nisa & Muhammad, 2021; Ragheb et al., 2021), or drug overdose (OD) (Fisher et al., 2023; Nasralah et al., 2020; Phan et al., 2017; Fan et al., 2017) as isolated phenomena. These approaches have yielded domain-specific insights and specialized detection techniques, establishing methodological foundations for computational analysis of psychological distress signals in digital contexts. Additionally, community-based detection approaches (Tébar & Gopalan, 2021; Wang et al., 2017a; Chancellor et al., 2016b) have demonstrated promising results by analyzing linguistic patterns within specific online groups, though these implementations remain relatively sparse in the literature.

However, these existing approaches exhibit significant limitations that constrain their effectiveness in real-world applications. First, the predominant focus on single behavioral categories fails to address the complex comorbidities and overlapping patterns frequently observed in at-risk individuals, who often exhibit multiple forms of self-destructive behaviors simultaneously. Second, the overwhelming concentration on English-language content (Scherr et al., 2020; Tébar & Gopalan, 2021; Sixto-García & Duarte-Melo, 2020) severely restricts applicability in multilingual environments where vulnerable communities communicate using culturally-specific expressions and coded terminology, creating substantial blind spots in global detection systems. Furthermore, the limited adoption of community-contextualized approaches neglects crucial social dynamics through which self-destructive ideation becomes normalized and reinforced, significantly reducing model sensitivity when confronted with the nuanced, evolving discourse of real-world at-risk communities. These constraints collectively highlight the need for more comprehensive, multilingual, and contextually-aware detection frameworks that can effectively identify concerning content across diverse cultural and linguistic contexts.

To address existing gaps in research and intervention, our study examines the Jirai (in English: landmine; in Chinese:地雷; in Japanese: じらい) community 1 —a transnational social media phenomenon spanning Chinese and Japanese online spaces that encompasses multiple forms of self-destructive behaviors simultaneously. This community represents an ideal case study for developing JiraiBench, as it presents unique challenges for content moderation systems and mental health interventions. What makes the Jirai community particularly valuable for our research is its simultaneous manifestation of self-destructive behaviors such as substance abuse, eating disorders, and self-harm—precisely the categories targeted by our annotation framework. This stands in contrast to previous research that typically focuses on single behavioral domains. Moreover, the Jirai community poses complex challenges due to its cross-border nature across differing regulatory environments, the use of coded language to evade standard monitoring algorithms, internal reinforcement mechanisms that intensify harmful behaviors, and the persistent stigma surrounding mental health issues in both Chinese and Japanese societies. These factors often divert vulner-

¹https://aesthetics.fandom.com/wiki/Jirai_Kei

able individuals toward alternative peer networks rather than seeking professional help (Niramaya & Filia, 2023).

By analyzing this bilingual community through a contextually aware approach, we demonstrate how language-specific nuances and community dynamics must be incorporated into detection systems—addressing a significant limitation of English-centric, behavior-isolated models that lack the cultural and linguistic sensitivity required for effective intervention in diverse global contexts.

Our contributions are summarized as follows:

- 1) We conducted comprehensive experiments in 4 state-of-the-art LLMs using 2 baseline configurations, systematically evaluating performance in both target languages with prompts in Chinese, Japanese, and English, revealing unexpected patterns of cross-cultural transfer.
- 2) We uncover a noteworthy emergent phenomenon in which Japanese instruction prompts consistently outperform Chinese prompts when processing Chinese content, suggesting important linguistic-cultural bridges in transnational content moderation tasks.
- 3) We investigate cross-lingual transfer capabilities by fine-tuning Qwen2.5 7B on Chinese data and demonstrate significant performance improvements on both source and target languages, particularly by improving detection of self-destructive behaviors in Japanese content without explicit Japanese training data.

2 Related Work

2.1 Social Media and Mental Health

Natural language processing (NLP) has long been a pivotal tool for researchers who studied mental health problems through textual data, ranging from conventional clinical records to contemporary digital platforms content. Social media was regarded as a valuable resource to understand users mental dynamics, with studies showing that such content carries detectable signals of mental disorders and that online activities can reflect individuals' pyschological states (Paul & Dredze, 2011; Coppersmith et al., 2014).

Among the considerable amount of NLP-based mental health studies, depression is the most discussed one due to its high prevalence and broad implications. It has been well established that individuals' mental states can be conveyed through language use (Chancellor & De Choudhury, 2020), one representative example of which is that depressed people tend to use first-person pronouns and negative words with a higher frequency (De Choudhury et al., 2013). The boundary of NLP research in mental health was also extended to other types as mental illness has become a shared, concerning issue for contemporary human beings. Post-Traumatic Stress Disorder (PTSD) (Murarka et al., 2021), Attention Deficit Hyperactivity Disorder (ADHD) (Guntuku et al., 2023), and other general problems have all been examined via language cues, such as references to trauma, heightened expressions of fear, expressions of worry, and rumination. These linguistic markers are usually emblematic of negative psychological conditions, exposing critical insights into how mental states manifest in languages (Teodorescu et al., 2023).

The evolution of NLP nurtured the growing research interest in this domain. As this field matured in mid-2010s, research focus shifted from domain-specific lexical analysis and correlation statistics to machine learning-based predictive models. Behavioral features, such as linguistic style, posting frequency, and social network attributes were engineered and then fed into classifiers, such as logistic regression (LR) and support vector machine (SVM), to detect relevant user-generated content (De Choudhury et al., 2013; Tsugawa et al., 2015).

With the introduction of transformer, transformer-based models revolutionized the research landscape in this area, bringing remarkable improvements in the detection task and outperformed earlier deep learning models (Jiang et al., 2020; Matero et al., 2019). In particular, specialized models like MentalBERT that were trained in a mental health-specific corpus have demonstrated an improved capability of identifying edged language patterns in people's mental health disclosures (Ji et al., 2022).

Although the prior methods have shown promising results, several key challenges persist. One recurring issue is data scarcity and quality. Clinical diagnostic data is normally private and scarce, while datasets populated with online posts were in the doubt of construct validity—the lack of a standardized assessment of each post not only introduces mislabeling risk but also complicates the process of results evaluation. Another pivotal issue lies in the peculiar, intricate linguistic patterns in posts involved with negative mental conditions. Usually, distress was expressed in a figurative or implicit way, where creative metaphors, sarcasm, and irony were communicated as an encoded language to describe the feelings (Coppersmith et al., 2014; Mendes & Caseli, 2024). Additionally, most research were established on English dataset with far fewer in other languages such as Chinese and Japanese (Cao et al., 2025) and models therein were trained on corpus constructed from single platform or a homogeneous demographic, consequently limiting models applicability to more diverse populations.

2.2 NLP for Self-Destructive Behaviors

Besides the shared attributes, targeting self-destructive behaviors differs remarkably from the task on general mental illness. Self-destructive behaviors that might incur detrimental and even life-threatening outcomes necessitate more accurate detection for taking preventive actions, while their unique linguistic patterns confront researchers with more challenges.

Flagging users on social media who reveal a tendency toward non-suicidal SH acts and suicidal ideation is a vital yet sensitive application of NLP. Studies reveal that the combination of linguistic signals from content, such as hopelessness, self-hate, and past suicidal attempts, coupled with online behavioral patterns greatly improve the models performance—and it usually gets better when instilled with domain knowledge (Zhang et al., 2024; Ng et al., 2023; Choudhury & Kıcıman, 2017). Some works focus specifically on SH that might include mentions of self-cutting or injury (Cliffe et al., 2021), where the incorporation of psychological lexicons helps models identify depressive expressions as warning sign.

Likewise, ED detection is another intractable task because the involved individuals barely explicitly state their conditions. Instead, such tendencies manifest through obsessive discussions of weight, food, calories, and body images, which makes the ingestion of specific knowledge essential to ensure models performance on the classification task accordingly (Chan et al., 2022).

Social media-based OD study is also one of the concerning areas that NLP is widely applied to (Wright et al., 2021). One unique challenge specific to this domain is the language ambiguity of drug references and the fast-evolving drug landscape, further complicating the construction of datasets—from identifying emerging drugs through obscure drug references to discerning the intent behind those drug-included posts. Annotating such data also requires expert assistance in analyzing if the post is truly indicative of substance abuse rather than casual innocuous mentioning.

Most recently, the surge of LLMs, such as GPT-4 (et el, 2024), PaLM (Chowdhery et al., 2022), and LLaMA (Touvron et al., 2023), have create new avenues for tasks in mental healthcare. LLMs demonstrate strong capabilities in distinguishing user-generated content related to SD behaviors and catching on the worsening psychological conditions of sufferers, such as disordered eating pathology, substance abuse, and suicidal ideation—even in zero-shot or few-shot settings (Stade et al., 2024). Based on their supremacy in understanding the linguistic nuances of the intense content of information on social media, such models can identify subtextual signals indicative of mental distress, enabling immediate interventions.

However, LLMs-based approach for self-destructive content detection is faced with generalizability obstacles that span across platforms, cultures, and languages thereof. Most mainstream LLMs were primarily trained on English-centric corpus, whereas materials in other languages only take a fairly small proportion of that. Even these state-of-the-art models struggle while adapting to multilingual environments featuring different languages and cultures—this task becomes trickier given the community-based, culture-dependent expressions. While LLMs excel at contextual understanding, the linguistic peculiarities

varying by users across platforms can imperil the models performance, especially when expressions are intentionally obfuscated to evade content moderation.

3 Dataset Construction

In this section, we describe the construction of JiraiBench dataset. We start with introducing the data collection and filtering process, then turning to the annotation.

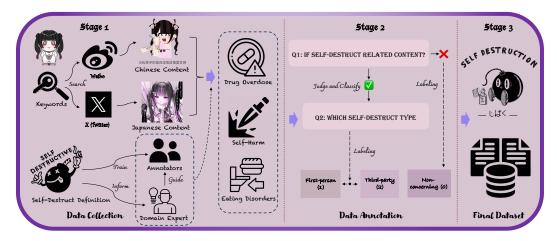


Figure 1: Illustration of JiraiBench dataset construction procedure. "0" indicating absence of targeted behaviors, "1" signifying first-person expressions, and "2" denoting third-party descriptions.

3.1 Data Collection and Cleaning

For the Chinese dataset, we implemented a keyword-based search approach to gather relevant posts from Sina Weibo², China's equivalent of X (formerly Twitter). Using specialized lexicons developed by domain experts in both languages for OD, ED, and SH, we identified posts that discuss self-destructive behaviors within the community. This process yielded a comprehensive Chinese dataset containing 10,419 potentially concerning posts. The lexicons were meticulously curated to include both explicit and implicit terminology commonly associated with each behavior type. Similarly, we applied the same methodological framework to construct the Japanese dataset, ensuring consistency between the collections. From X^3 , we collected 5,000 tweets, with varying associations to the three behaviors of interest. Both datasets underwent an identical data cleansing pipeline to remove irrelevant content, including advertisements, duplicate entries, excessively short posts lacking meaningful information, and other noise. In accordance with platform policies and to maintain user privacy, we eliminated all usernames, gender information, and other personally identifiable information. We present randomly selected data examples in Appendix A.

3.2 Data Annotation

Our annotation protocol employs a multidimensional framework to identify self-destructive behaviors in social media texts, establishing three distinct categories: OD, ED, and SH. This breakdown enables finer-grained category-based analysis. For each post, the annotators evaluated the content using a three-point ordinal scale: "0" indicating absence of targeted behaviors, "1" signifying first-person expressions, and "2" denoting third-party descriptions - a distinction that provides critical contextual information for analysis and intervention systems.

²https://weibo.com/

³https://x.com/

The annotation process followed a systematic methodology in which annotators first performed comprehensive readings of each post, including textual content and paralinguistic markers, before identifying potentially harmful content. Annotators were trained to distinguish genuine expressions of harmful tendencies from figurative language, with specific guidelines established for ambiguous cases. We developed precise annotation criteria for each dimension. OD identified substance misuse or dangerous drug consumption; ED captured extreme food restrictions, binge-purge behaviors, or unhealthy weight fixations; and SH encompassed suicidal ideation or self-injury behaviors. Each dimension was evaluated independently, allowing for multi-label classification when appropriate.

For this research, we recruited a team of six annotators, evenly divided between Chinese and Japanese, and spent 100 hours in annotators training and labeling on each side. For each language, the team consisted of two native speakers and one domain expert, resulting in three annotators for Chinese (including two native Chinese speakers and one domain expert) and three annotators for Japanese (including two native Japanese speakers and one domain expert). All annotators received equitable compensation at minimum wage levels applicable in their respective regions (Hong Kong SAR for Chinese and Japan for Japanese). Annotator disagreements were systematically resolved through a combination of majority voting and expert supervision, ensuring annotation consistency. We evaluated inter-annotator reliability using both pairwise (Cohen's Kappa) and overall (Fleiss' Kappa) agreement metrics. The results demonstrate substantial agreement across all annotation dimensions, with average Cohen's Kappa values ranging from 0.69 to 0.78 and Fleiss' Kappa values consistently above 0.68 for all three categories. These robust agreement scores indicate strong consistency among annotators, confirming the reliability of our annotation framework for the detection of self-destructive behaviors. Specific annotation guidelines can be found in the Appendix B.

3.3 Data Composition

Our analysis includes two datasets: 10,419 posts from the Chinese social platform Sina Weibo and 5,000 posts from Japanese X (formerly Twitter). The Chinese dataset shows higher content related rates in all categories, with OD-related posts that contain 30. 55% first-person expressions compared to only 3.82% in the Japanese dataset. Similarly, the content of ED in the Chinese data set showed 15.04% first-person expressions versus 3.14% in the Japanese dataset. SH content demonstrated more comparable distributions, with first-person expressions comprising 10.27% of Chinese posts and 8.36% of Japanese posts. Table 1 provides a comprehensive breakdown of both datasets across all behavior categories and label types.

Behavior Category	Label Type	Chinese Dataset		Japanese Dataset	
2 charter entegery	20001 1) PC	Count	Percentage	Count	Percentage
Drug Overdose (OD)	Non-concerning (0)	6,268	60.16%	4,706	94.12%
	First-person (1)	3,183	30.55%	191	3.82%
	Third-party (2)	968	9.29%	103	2.06%
Eating disorders (ED)	Non-concerning (0)	8,605	82.59%	4,572	91.44%
	First-person (1)	1,567	15.04%	157	3.14%
	Third-party (2)	247	2.37%	271	5.42%
Self-Harming (SH)	Non-concerning (0)	8,924	85.65%	4,427	88.54%
	First-person (1)	1,070	10.27%	418	8.36%
	Third-party (2)	425	4.08%	155	3.10%
Total Posts	-	10,419	100%	5,000	100%

Table 1: Comparison of Chinese and Japanese Datasets for Concerning Behaviors

4 Experiments

Our experimental framework systematically evaluates the performance of LLMs in detecting self-destructive behaviors in social media content in multiple languages and test conditions. We employ four state-of-the-art language models, Llama-3.1 8B (Meta, 2024), Qwen-2.5 7B (Qwen et al., 2025), DeepSeek-v3 (DeepSeek-AI, 2025), as well as our finetuned JiraiLLM-Qwen. We then structure our investigations around three complementary experimental paradigms.

In our initial experimental design, we attempted to include GPT-40 as a baseline; however, the model consistently refused to perform classification tasks involving self-destructive content despite varied prompting strategies. This limitation highlights significant limitations in the evaluation of closed source models for the detection of sensitive content and underscores the need for specialized research interfaces that balance safety mechanisms with legitimate research on harmful content detection.

4.1 Baseline

The baseline experiments establish fundamental performance benchmarks across both Chinese and Japanese corpora under zero-shot and few-shot learning conditions. For zero-shot evaluation, models receive task instructions without exemplars, requiring them to leverage pre-trained knowledge for classification across our three-dimensional annotation scheme. The few-shot configuration provides two examples representing diverse manifestations of self-destructive behaviors with balanced representation across categories. To avoid selective bias, all examples shown in the data are randomly sampled from our dataset. We independently calculated precision, recall, and F1 scores for each dimension to assess overall classification effectiveness and identify language-specific processing disparities. Prompts are provided in Appendix C.

4.2 Crosslingual Transfer

The examination of the effectiveness of cross-lingual transfer in our study involved fine-tuning Qwen2.5 with 3,000 randomly sampled data points from a Chinese dataset utilizing Chinese prompts, resulting in the development of JiraiLLM-Qwen. Our comprehensive evaluation framework assessed the model's performance across both the source Chinese dataset and the target Japanese dataset, providing empirical insights into the model's capacity to transfer linguistic knowledge between related but distinct language systems without explicit training on the target language. This investigation offers valuable insight into the capabilities of cross-linguistic generalization in LLMs, particularly in East Asian language contexts where shared writing systems and linguistic features may facilitate knowledge transfer despite significant structural and lexical differences between languages. Detailed training parameters and hyperparameter configurations are attached in the appendix D.

4.3 Evaluation Metric

To align with the established research norm (Yang et al., 2024), we use the Macro F1 score as the evaluation metrics for our self-destructive behavior detection task. The metric assesses the model's performance in successfully identifying self-destructive behaviors.

5 Result and Discussion

Table 2 presents the self-destructive behavior detection outcomes for all models, showing that Jirai-qwen achieves the highest performance on Chinese data across all three detection dimensions. However, both open-source models exhibit a remarkable pattern where Japanese instruction prompts consistently outperform Chinese prompts when processing Chinese content, despite Japanese not being the native language of the content. This indicates a significant cross-cultural transfer effect in self-destructive content detection.

Dataset	Prompt	Method	Task	Qwen2.5 7B	Llama3.1 8B	DeepSeek-v3	Jirai-Qwen	Random
C		zero-shot	OD	0.5052	0.3598	0.5478	0.6398	0.2504
			ED	0.4706	0.3349	0.4163	0.6503	0.3015
	Chinese		SH	0.3927	0.3232	0.4205	0.5533	0.3076
	Crimicsc		OD	0.4190	0.4400	-	-	0.2504
		two-shot	ED	0.2951	0.3590	-	-	0.3015
			SH	0.4284	0.3714	-	-	0.3076
			OD	0.5226	0.3969	0.5229	0.6371	0.2504
		zero-shot	ED	0.5431	0.3403	0.3962	0.6069	0.3015
Chinese	Japanese		SH	0.4154	0.3240	0.3670	0.5402	0.3076
	Japanese		OD	0.3078	0.2503	-	-	0.2504
		two-shot	ED	0.3470	0.3014	-	-	0.3015
			SH	0.3118	0.3081	-	-	0.3076
			OD	0.4796	0.3516	0.5087	0.4769	0.2504
		zero-shot	ED	0.4023	0.2771	0.4148	0.6173	0.3015
	English		SH	0.3933	0.3164	0.4286	0.5993	0.3076
	Liighsii	two-shot	OD	0.3304	0.3352	-	-	0.2504
			ED	0.2223	0.2173	-	-	0.3015
			SH	0.4278	0.2773	-	-	0.3076
			OD	0.3813	0.2869	0.5521	0.3167	0.3232
	Chinese	zero-shot	ED	0.4139	0.2573	0.4097	0.4163	0.3184
			SH	0.4241	0.3280	0.4159	0.3114	0.3131
	Cimiese		OD	0.4087	0.3254	-	-	0.3232
		two-shot	ED	0.4172	0.2459	-	-	0.3184
			SH	0.4319	0.3448	-	-	0.3131
	Japanese		OD	0.4059	0.2430	0.5974	0.5117	0.3232
		zero-shot	ED	0.4665	0.2000	0.4585	0.5761	0.3184
Japanese			SH	0.4292	0.2255	0.4782	0.4840	0.3131
		two-shot	OD	0.3428	0.3232	-	-	0.3232
			ED	0.3684	0.3184	-	-	0.3184
			SH	0.3131	0.3130	-	-	0.3131
	E 1:-1.		OD	0.3683	0.2385	0.5335	0.4939	0.3232
		zero-shot E	ED	0.3777	0.2661	0.4282	0.5328	0.3184
			SH	0.4302	0.3028	0.4198	0.4738	0.3131
	English		OD	0.4210	0.2141	-	-	0.3232
		two-shot	ED	0.3940	0.2109	-	-	0.3184
			SH	0.4648	0.2795	-	-	0.3131

Table 2: Performance comparison across models, datasets, prompts, and methods, with tasks organized by rows. Red values indicate the best approach in Chinese tasks; Green values indicate the best approach in Japanese tasks; and Cyan values highlight emergent cross-cultural transfer behavior, which are statistically significantly better than their Chinese zero-shot counterparts.

5.1 Effects on Different Instruction Language

Our experimental findings reveal compelling emergent cross-cultural transfer patterns that challenge conventional assumptions about language-model alignment in content moderation tasks. The observed superiority of Japanese instruction prompts when processing Chinese content, especially in a zero-shot scenario, demonstrates a fascinating linguistic-cultural bridge effect that transcends straightforward language matching. This phenomenon manifests consistently across multiple model architectures, suggesting a systematic cross-cultural transfer mechanism rather than model-specific behaviorWendler et al. (2024).

The effectiveness of Japanese instructions for the moderation of Chinese content probably stems from the cultural relationship between these language communities. Given that Jirai cultural frameworks originated in Japan before spreading to Chinese-speaking regions, Japanese prompts appear to activate more nuanced cultural schemata relevant to self-destructive behaviors. These culturally embedded frames potentially guide model attention toward subtle linguistic patterns that Chinese instructions fail to adequately highlight, despite being the native language of the content.

Our findings on cross-cultural transfer patterns in self-destructive content detection align with mechanistic interpretability research by Wendler et al., who identified a three-phase processing pattern in Llama-2 models handling multilingual tasks. Their analysis revealed

that latent embeddings in middle processing layers already encode appropriate concepts but consistently assign higher probability to English tokens than to target language equivalents—even when prompted in non-English languages. This computational evidence supports our observation that Japanese instruction prompts outperform Chinese prompts when processing Chinese content. Wendler et al.'s research suggests LLMs process information through an English-biased conceptual layer that enables effective cross-cultural transfer between Japanese and Chinese due to their shared cultural frameworks rather than linguistic similarities. Their dimensional analysis suggests that shared logographic writing systems create additional pathways for cultural concepts to traverse linguistic boundaries—particularly important when detecting nuanced psychological phenomena like self-destructive behaviors where semantic representations may activate more effectively through culturally proximate instruction languages.

This finding has broader implications that could potentially generalize to many similar cross-cultural scenarios where shared cultural history creates linguistic bridges between instruction languages and target behaviors. In domains ranging from mental health screening to content moderation, using instruction languages with historical-cultural connections to target phenomena might enhance detection capabilities beyond what standard native language approaches achieve. This suggests an important methodological consideration for multilingual AI deployment: the optimal instruction language may not be the target dataset language, but rather one that activates relevant cultural schema for the specific detection task in question.

5.2 Effects on Zero-shot VS Few-shot prompting

The contrasting performance patterns between zero-shot and few-shot methodologies in our experimental framework reveal nuanced dynamics in the detection of cross-cultural self-destructive behavior. Our analysis demonstrates that zero-shot approaches consistently outperform few-shot methods across most model language configurations, contradicting conventional wisdom regarding few-shot learning benefits. This phenomenon likely stems from the culturally embedded nature of self-destructive behaviors, which manifest through subtle linguistic and contextual patterns that resist straightforward exemplification. The cultural scheme underlying self-destructive behaviors in East Asian contexts, particularly within Jirai cultural frameworks originating from Japan, involve deeply situated knowledge that few-shot exemplars struggle to adequately represent. These cultural understandings encompass complex sociolinguistic signals, indirect expressions, and culturally specific metaphors that may be entirely absent from model training distributions.

The performance degradation observed in few-shot settings potentially indicates interference effects, whereby provided examples inadvertently constrain model attention to narrow manifestations of self-destructive ideation that fail to generalize across the diverse expression patterns present in authentic data (Yang et al., 2022). This limitation appears particularly pronounced when the few-shot examples lack the cultural depth necessary to activate appropriate interpretive frameworks. The complex interrelationship between instruction language and exemplar effectiveness further compounds these challenges, suggesting that the cultural alignment between prompt language and dataset requires more sophisticated calibration than few-shot learning readily accommodates.

6 Conclusion

JiraiBench represents the first bilingual benchmark for evaluating LLMs' capability to detect self-destructive content across Chinese and Japanese online communities. Our comprehensive experiments across four state-of-the-art models reveal significant limitations in current systems' effectiveness in identifying harmful content within these linguistically and culturally complex environments. The observed emergent pattern—where Japanese instruction prompts consistently outperform Chinese prompts for Chinese content detection—underscores critical cultural-linguistic alignment effects stemming from the Jirai phenomenon's Japanese origins. This counterintuitive discovery demonstrates that cultural proximity can sometimes outweigh linguistic similarity in cross-lingual detection tasks.

Future work should focus on developing more robust cross-cultural transfer learning methodologies, expanding benchmark datasets to include additional languages and cultural contexts, and incorporating more nuanced annotation schemes that capture the complex manifestations of self-destructive behaviors across diverse communities.

Ethical Statement

This research addresses the complex ethical terrain surrounding self-destructive behavior detection in multilingual online communities. Our work leverages publicly accessible social media data containing sensitive mental health content, including drug overdose , eating disorders , and self-harm, necessitating rigorous ethical considerations throughout our methodological framework.

We acknowledge inherent sampling limitations in our approach, as user-generated content on social media platforms reflects demographic, linguistic, and cultural disparities that may affect the generalizability of our findings. The Jirai community itself represents a specific transnational online subculture whose linguistic patterns and behavioral expressions may differ from those in other vulnerable populations or platforms. These constraints are transparently documented to contextualize our results appropriately.

Our data collection and annotation protocols prioritized ethical treatment of both content and annotators. All six annotators received comprehensive training in recognizing harmful content patterns while maintaining appropriate emotional distance, with regular debriefing sessions throughout the annotation process. To reflect the emotionally intensive nature of content evaluation and the specialized expertise required, all annotators received compensation substantially exceeding minimum wage standards in their respective regions (Hong Kong SAR for Chinese and Japan for Japanese).

We implemented stringent privacy preservation measures in strict adherence to platform policies. All datasets underwent comprehensive desensitization procedures to eliminate personally identifiable information, including usernames, timestamps, location data, and other potential identifiers. Given the ethical considerations surrounding informed consent, protection of user privacy, and potential stigmatization of the studied community, we have implemented a controlled data release policy wherein both language datasets will be available exclusively upon request to verified academic and research institutions.

Our research contributes primarily to enhancing content moderation systems that increasingly incorporate AI technologies. By examining cross-lingual and cross-cultural dimensions of self-destructive behavior detection, we aim to develop more culturally informed approaches that can better support vulnerable individuals across linguistic boundaries. This work aligns with broader ethical imperatives in the NLP community to develop responsible AI systems that can identify concerning content patterns while respecting principles of privacy, cultural sensitivity, and appropriate intervention methodologies.

References

Roy F Baumeister and Steven J Scher. Self-defeating behavior patterns among normal individuals: review and analysis of common self-destructive tendencies. *Psychological bulletin*, 104(1):3, 1988.

Yuchen Cao, Jianglai Dai, Zhongyan Wang, Yeyubei Zhang, Xiaorui Shen, Yunchong Liu, and Yexin Tian. Machine learning approaches for depression detection on social media: A systematic review of biases and methodological challenges. *Journal of Behavioral Data Science*, 5(1):1–36, February 2025. ISSN 2574-1284. doi: 10.35566/jbds/caoyc. URL http://dx.doi.org/10.35566/jbds/caoyc.

William W Chan, Ellen E Fitzsimmons-Craft, Arielle C Smith, Marie-Laure Firebaugh, Lauren A Fowler, Bianca DePietro, Naira Topooco, Denise E Wilfley, C Barr Taylor, and Nicholas C Jacobson. The challenges in designing a prevention chatbot for eating disorders: observational study. *JMIR Formative Research*, 6(1):e28003, 2022.

- Stevie Chancellor and Munmun De Choudhury. Methods in predictive techniques for mental health status on social media: A critical review. *npj Digital Medicine*, 3:43, 2020. doi: 10.1038/s41746-020-0233-7.
- Stevie Chancellor, Zhiyuan Lin, and Munmun De Choudhury. "this post will just get taken down" characterizing removed pro-eating disorder social media content. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, pp. 1157–1162, 2016a.
- Stevie Chancellor, Zhiyuan Lin, Erica L Goodman, Stephanie Zerwas, and Munmun De Choudhury. Quantifying and predicting mental illness severity in online pro-eating disorder communities. In *Proceedings of the 19th ACM conference on computer-supported cooperative work & social computing*, pp. 1171–1184, 2016b.
- Munmun De Choudhury and Emre Kıcıman. The language of social support in social media and its effect on suicidal ideation risk. *Proceedings of the ... International AAAI Conference on Weblogs and Social Media. International AAAI Conference on Weblogs and Social Media*, 2017: 32–41, 2017. URL https://api.semanticscholar.org/CorpusID:19108547.
- Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, Parker Schuh, Kensen Shi, Sasha Tsvyashchenko, Joshua Maynez, Abhishek Rao, Parker Barnes, Yi Tay, Noam Shazeer, Vinodkumar Prabhakaran, Emily Reif, Nan Du, Ben Hutchinson, Reiner Pope, James Bradbury, Jacob Austin, Michael Isard, Guy Gur-Ari, Pengcheng Yin, Toju Duke, Anselm Levskaya, Sanjay Ghemawat, Sunipa Dev, Henryk Michalewski, Xavier Garcia, Vedant Misra, Kevin Robinson, Liam Fedus, Denny Zhou, Daphne Ippolito, David Luan, Hyeontaek Lim, Barret Zoph, Alexander Spiridonov, Ryan Sepassi, David Dohan, Shivani Agrawal, Mark Omernick, Andrew M. Dai, Thanumalayan Sankaranarayana Pillai, Marie Pellat, Aitor Lewkowycz, Erica Moreira, Rewon Child, Oleksandr Polozov, Katherine Lee, Zongwei Zhou, Xuezhi Wang, Brennan Saeta, Mark Diaz, Orhan Firat, Michele Catasta, Jason Wei, Kathy Meier-Hellstern, Douglas Eck, Jeff Dean, Slav Petrov, and Noah Fiedel. Palm: Scaling language modeling with pathways, 2022. URL https://arxiv.org/abs/2204.02311.
- Charlotte Cliffe, Azadeh Seyedsalehi, Katerina Vardavoulia, André Bittar, Sumithra Velupillai, Hitesh Shetty, Ulrike Schmidt, and Rina Dutta. Using natural language processing to extract self-harm and suicidality data from a clinical sample of patients with eating disorders: a retrospective cohort study. *BMJ Open*, 11(12):e053808, 2021. doi: 10.1136/bmjopen-2021-053808. URL https://doi.org/10.1136/bmjopen-2021-053808.
- Glen Coppersmith, Mark Dredze, and Craig Harman. Quantifying mental health signals in twitter. In *Proceedings of the Workshop on Computational Linguistics and Clinical Psychology:* From Linguistic Signal to Clinical Reality, pp. 51–60, 2014. URL https://aclanthology.org/W14-3207/.
- Munmun De Choudhury, Michael Gamon, Scott Counts, and Eric Horvitz. Predicting depression via social media. *Proceedings of the International AAAI Conference on Web and Social Media*, 7:128–137, 2013.
- DeepSeek-AI. Deepseek-v3 technical report, 2025. URL https://arxiv.org/abs/2412.19437.
- OpenAI et el. Gpt-4 technical report, 2024. URL https://arxiv.org/abs/2303.08774.
- Yujie Fan, Yiming Zhang, Yanfang Ye, Xin Li, and Wanhong Zheng. Social media for opioid addiction epidemiology: Automatic detection of opioid addicts from twitter and case studies. In *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*, pp. 1259–1267, 2017.
- Robert W Firestone and Richard H Seiden. Suicide and the continuum of self-destructive behavior. *Journal of American College Health*, 38(5):207–213, 1990.

- Andrew Fisher, Matthew Maclaren Young, Doris Payer, Karen Pacheco, Chad Dubeau, and Vijay Mago. Automating detection of drug-related harms on social media: machine learning framework. *Journal of medical internet research*, 25:e43630, 2023.
- Sharath Chandra Guntuku, Jami F Young, Daniel Romer, Lyle Ungar, and Russell Ramsay. Exploring the behavior of users with attention deficit hyperactivity disorder on twitter: Observational study. *Journal of Medical Internet Research*, 25:e43439, 2023. doi: 10.2196/43439. URL https://www.jmir.org/2023/1/e43439.
- Shaoxiong Ji, Tianlin Zhang, Luna Ansari, Jie Fu, Prayag Tiwari, and Erik Cambria. Mental-BERT: Publicly available pretrained language models for mental healthcare. In Nicoletta Calzolari, Frédéric Béchet, Philippe Blache, Khalid Choukri, Christopher Cieri, Thierry Declerck, Sara Goggi, Hitoshi Isahara, Bente Maegaard, Joseph Mariani, Hélène Mazo, Jan Odijk, and Stelios Piperidis (eds.), *Proceedings of the Thirteenth Language Resources and Evaluation Conference*, pp. 7184–7190, Marseille, France, June 2022. European Language Resources Association. URL https://aclanthology.org/2022.lrec-1.778/.
- Zhengping Jiang, Sarah Ita Levitan, Jonathan Zomick, and Julia Hirschberg. Detection of mental health from Reddit via deep contextualized representations. In Eben Holderness, Antonio Jimeno Yepes, Alberto Lavelli, Anne-Lyse Minard, James Pustejovsky, and Fabio Rinaldi (eds.), *Proceedings of the 11th International Workshop on Health Text Mining and Information Analysis*, pp. 147–156, Online, November 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.louhi-1.16. URL https://aclanthology.org/2020.louhi-1.16/.
- Matthew Matero, Akash Idnani, Youngseo Son, Salvatore Giorgi, Huy Vu, Mohammad Zamani, Parth Limbachiya, Sharath Chandra Guntuku, and H. Andrew Schwartz. Suicide risk assessment with multi-level dual-context language and bert. In *Proceedings of the Sixth Workshop on Computational Linguistics and Clinical Psychology*, pp. 142–147. Association for Computational Linguistics, 2019. URL https://aclanthology.org/W19-3005/.
- Augusto R. Mendes and Helena Caseli. Identifying fine-grained depression signs in social media posts. In Nicoletta Calzolari, Min-Yen Kan, Veronique Hoste, Alessandro Lenci, Sakriani Sakti, and Nianwen Xue (eds.), *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024)*, pp. 8594–8604, Torino, Italia, May 2024. ELRA and ICCL. URL https://aclanthology.org/2024.lrec-main.754/.
- Meta. The llama 3 herd of models, 2024. URL https://arxiv.org/abs/2407.21783.
- Markus Moessner, Johannes Feldhege, Markus Wolf, and Stephanie Bauer. Analyzing big data in social media: Text and network analyses of an eating disorder forum. *International Journal of Eating Disorders*, 51(7):656–667, 2018.
- Ankita Murarka, Aravind Sengadu Suresh, Aayushi Lalwani, Kajal Bajaj, Muskan Garg, and Sakshi Srivastava. Detection and classification of mental illnesses on social media using roberta. In *Proceedings of the 12th International Workshop on Health Text Mining and Information Analysis*, pp. 59–68, 2021. URL https://aclanthology.org/2021.louhi-1.7.
- Tareq Nasralah, Omar El-Gayar, and Yong Wang. Social media text mining framework for drug abuse: development and validation study with an opioid crisis case analysis. *Journal of medical Internet research*, 22(8):e18350, 2020.
- Ka Chung Ng, Ping Fan Ke, Mike KP So, and Kar Yan Tam. Augmenting fake content detection in online platforms: A domain adaptive transfer learning via adversarial training approach. *Production and Operations Management*, 32(7):2101–2122, 2023.
- Kinanti Kanya Niramaya and Filia Filia. New phenomena in japanese youth language: Contrary meaning of pien. *International Review of Humanities Studies*, 7(2):12, 2023.
- Michael J. Paul and Mark Dredze. You are what you tweet: Analyzing twitter for public health. In *Proceedings of the Fifth International AAAI Conference on Weblogs and Social Media*, pp. 265–272, 2011. URL https://www.aaai.org/ocs/index.php/ICWSM/ICWSM11/paper/view/2880.

- Nhathai Phan, Soon Ae Chun, Manasi Bhole, and James Geller. Enabling real-time drug abuse detection in tweets. In 2017 IEEE 33rd international conference on data engineering (ICDE), pp. 1510–1514. IEEE, 2017.
- Qwen, :, An Yang, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chengyuan Li, Dayiheng Liu, Fei Huang, Haoran Wei, Huan Lin, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Yang, Jiaxi Yang, Jingren Zhou, Junyang Lin, Kai Dang, Keming Lu, Keqin Bao, Kexin Yang, Le Yu, Mei Li, Mingfeng Xue, Pei Zhang, Qin Zhu, Rui Men, Runji Lin, Tianhao Li, Tianyi Tang, Tingyu Xia, Xingzhang Ren, Xuancheng Ren, Yang Fan, Yang Su, Yichang Zhang, Yu Wan, Yuqiong Liu, Zeyu Cui, Zhenru Zhang, and Zihan Qiu. Qwen2.5 technical report, 2025. URL https://arxiv.org/abs/2412.15115.
- Waleed Ragheb, Jerome Aze, Sandra Bringay, and Maximilien Servajean. Negatively correlated noisy learners for at-risk user detection on social networks: A study on depression, anorexia, self-harm, and suicide. *IEEE Transactions on Knowledge and Data Engineering*, 35 (1):770–783, 2021.
- Sebastian Scherr, Florian Arendt, Thomas Frissen, and José Oramas M. Detecting intentional self-harm on instagram: development, testing, and validation of an automatic image-recognition algorithm to discover cutting-related posts. *Social science computer review*, 38 (6):673–685, 2020.
- José Sixto-García and Ana Duarte-Melo. Self-destructive content in university teaching: new challenge in the digital competence of educators. *Communication & Society*, 33(3): 187–199, 2020.
- Elizabeth C. Stade, Shannon Wiltsey Stirman, Lyle H. Ungar, Cody L. Boland, H. Andrew Schwartz, David B. Yaden, João Sedoc, Robert J. DeRubeis, Robb Willer, and Johannes C. Eichstaedt. Large language models could change the future of behavioral healthcare: a proposal for responsible development and evaluation. *npj Mental Health Research*, 3 (12), 2024. doi: 10.1038/s44184-024-00056-z. URL https://www.nature.com/articles/s44184-024-00056-z.
- Blanca Tébar and Anandha Gopalan. Early detection of eating disorders using social media. In 2021 IEEE/ACM Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE), pp. 193–198. IEEE, 2021.
- Daniela Teodorescu, Tiffany Cheng, Alona Fyshe, and Saif Mohammad. Language and mental health: Measures of emotion dynamics from text as linguistic biosocial markers. In Houda Bouamor, Juan Pino, and Kalika Bali (eds.), *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pp. 3117–3133, Singapore, December 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.emnlp-main.188. URL https://aclanthology.org/2023.emnlp-main.188/.
- Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, Aurelien Rodriguez, Armand Joulin, Edouard Grave, and Guillaume Lample. Llama: Open and efficient foundation language models, 2023. URL https://arxiv.org/abs/2302.13971.
- Sho Tsugawa, Yusuke Kikuchi, Fumio Kishino, Kenji Nakajima, Yasuhide Itoh, and Hiroyuki Ohsaki. Recognizing depression from twitter activity. *Proceedings of the ACM CHI Conference on Human Factors in Computing Systems*, pp. 3187–3196, 2015. doi: 10.1145/2702123.2702280.
- Qamar Un Nisa and Rafi Muhammad. Towards transfer learning using bert for early detection of self-harm of social media users. *Proceedings of the Working Notes of CLEF*, pp. 21–24, 2021.
- Bessel A Van der Kolk, J Christopher Perry, and Judith Lewis Herman. Childhood origins of self-destructive behavior. *American journal of Psychiatry*, 148(12):1665–1671, 1991.

Tao Wang, Markus Brede, Antonella Ianni, and Emmanouil Mentzakis. Detecting and characterizing eating-disorder communities on social media. In *Proceedings of the Tenth ACM International conference on web search and data mining*, pp. 91–100, 2017a.

Yilin Wang, Jiliang Tang, Jundong Li, Baoxin Li, Yali Wan, Clayton Mellina, Neil O'Hare, and Yi Chang. Understanding and discovering deliberate self-harm content in social media. In *Proceedings of the 26th international conference on World Wide Web*, pp. 93–102, 2017b.

Chris Wendler, Veniamin Veselovsky, Giovanni Monea, and Robert West. Do llamas work in English? on the latent language of multilingual transformers. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar (eds.), *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 15366–15394, Bangkok, Thailand, August 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.acl-long. 820. URL https://aclanthology.org/2024.acl-long.820/.

Austin P. Wright, Christopher M. Jones, Duen Horng Chau, R. Matthew Gladden, and Steven A. Sumner. Detection of emerging drugs involved in overdose via diachronic word embeddings of substances discussed on social media. *Journal of Biomedical Informatics*, 119:103824, 2021. ISSN 1532-0464. doi: https://doi.org/10.1016/j.jbi.2021.103824. URL https://www.sciencedirect.com/science/article/pii/S1532046421001532.

Chenghao Yang, Tuhin Chakrabarty, Karli Hochstatter, Melissa Slavin, Nabila El-Bassel, and Smaranda Muresan. Identifying self-disclosures of use, misuse and addiction in community-based social media posts. In Kevin Duh, Helena Gomez, and Steven Bethard (eds.), *Findings of the Association for Computational Linguistics: NAACL* 2024, pp. 2507–2521, Mexico City, Mexico, June 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.findings-naacl.161. URL https://aclanthology.org/2024.findings-naacl.161/.

Jingfeng Yang, Haoming Jiang, Qingyu Yin, Danqing Zhang, Bing Yin, and Diyi Yang. SEQZERO: Few-shot compositional semantic parsing with sequential prompts and zero-shot models. In Marine Carpuat, Marie-Catherine de Marneffe, and Ivan Vladimir Meza Ruiz (eds.), Findings of the Association for Computational Linguistics: NAACL 2022, pp. 49–60, Seattle, United States, July 2022. Association for Computational Linguistics. doi: 10. 18653/v1/2022.findings-naacl.5. URL https://aclanthology.org/2022.findings-naacl.5/.

Dongsong Zhang, Lina Zhou, Jie Tao, Tingshao Zhu, and Guodong Gao. Ketch: a knowledge-enhanced transformer-based approach to suicidal ideation detection from social media content. *Information Systems Research*, 2024.

A Data Example

We present randomly selected data examples in Table 3.

B Annotation Guidelines

B.1 Annotation Objectives and Framework

We conducted independent annotation for each social media post across three dimensions:

- 1. **Drug Overdose (OD)**: Content containing drug overdose/misuse-related self-harm or extremely dangerous behaviors.
- 2. **Eating Disorders (ED)**: Content containing eating disorder tendencies, such as anorexia, binge eating, or purging behaviors.
- 3. **Self-harm or Suicidal Ideation (SH)**: Content containing self-injury, suicidal thoughts, or suicide plans.

Category	Chinese Example	Japanese Example
Overdose (OD)	喜欢ymsf的濒死感。每次o都想写遗书给朋友留点谷。(I like the near-death feeling from taking Dextromethorphan. Every time I overdose, I want to write a suicide note and leave some final words to my friends.)	ODもアムカも、やってみようかなくらいの気持ちだわ。(I feel like I might try an overdose on amoxicillin (Amca), just considering it a bit)
Eating Disorder (ED)	暴食后的催吐让人恶心,父母的控制欲令我窒息。(Purging after binge eating makes me sick, and my over-controlling parents suffocate me.)	昨日から食べても食べても吐いてしまうくほ (Since yesterday, no matter how much I eat, I keep throwing up")
Self- Harm (SH)	每次划开手腕的时候,那种痛感反而让我感到平静。(Every time I cut my wrist, the pain actually makes me feel calm.)	誰も気づかないように、太ももを切った。痛みだけが本当の感情。(I cut my thigh where no one would notice. The pain is the only real feeling.)

Table 3: Examples of Self-Destructive Content Categories in Chinese and Japanese

For each category (OD, ED, SH), annotation values were assigned as follows:

- 0: No indication of the targeted behavior in the post
- 1: Post implies/reveals the poster's own tendencies in this category (or potential tendencies)
- 2: Third-party narratives or comments about this category (not the poster's own behavior or tendencies)

Note: If a post received a value of 0 across all three categories (OD, ED, SH), it was still retained in the dataset (indicating the post did not manifest any self-destructive/self-harm related content).

B.2 Annotation Procedure

B.2.1 Complete Reading

- Read the entire post content, including text, emoticons/emojis, or punctuation that might affect semantics.
- For lengthy posts, focus on keywords or contexts related to drugs, diet, bodily harm/suicide, etc.

B.2.2 Identification and Classification

- Determine whether the post relates to any of the following categories: OD, ED, SH.
- If multiple content types are mentioned (e.g., "excessive weight loss + self-harm"), each relevant category must be independently assessed and annotated.
- For uncertain or ambiguous mentions, use contextual information to infer whether they truly indicate tendencies or are merely other descriptions (e.g., allusions, metaphors, jokes).

B.2.3 Distinguishing Between Poster vs. Third Party

- **Tendencies/behaviors occurring to the poster**: If it is clearly evident that the author is discussing or revealing their own behaviors or emotions, mark as "1".
- Only mentioning others' experiences or public events: If the post primarily describes third parties (friends, family, celebrities, news, etc.), not the author themselves, mark as "2".

• Completely lacking such content: If no suggestions or comments about OD, ED, or SH appear, mark as "0".

B.2.4 Concurrent Annotation

• As this employs multi-label annotation, assign values 0/1/2 to each of the three categories (OD, ED, SH), resulting in three annotation values.

B.3 Detailed Annotation Guidelines and Examples

The following examples are intended to illustrate judgment principles; actual annotation should incorporate more contextual information.

B.3.1 Drug Overdose (OD)

• 0: No tendency

- Posts completely lacking mention of drugs, narcotics, overdose, etc.
- Example: "I'm in a good mood today, went for a run."

• 1: Poster's own OD tendency

- Posts mentioning the author's own drug overdose or misuse behaviors, intentions, or plans.
- Example: "I've been relying on taking many sedatives to sleep lately, I wish I could just take enough at once."

• 2: Third-party OD comments

- Posts mentioning others' drug overdose or social incidents, not the author's actions.
- Example: "My friend was hospitalized yesterday for taking too many sleeping pills, it's terrifying."

B.3.2 Eating Disorder (ED)

0: No tendency

- Posts without any eating disorder-related expressions.
- Example: "I made steak and salad today, it was delicious."

• 1: Poster's own ED tendency

- Posts implying or directly stating the author's eating disorder, such as deliberate fasting, purging, excessive dieting, etc.
- Example: "I haven't eaten anything for three days, I feel like I'm about to reach my ideal weight."

• 2: Third-party ED comments

- Mentions of others having eating disorder behaviors or discussions of others/social cases.
- Example: "My roommate frequently binges and then purges, I'm a bit worried about her."

B.3.3 Self-Harm or Suicidal Ideation (SH)

• 0: No tendency

- Completely lacking any hint of self-harm, suicidal thoughts, or behaviors.
- Example: "I made plans with friends to see a movie today, feeling very happy."

• 1: Poster's own self-harm/suicidal tendency

Clearly mentioning the author's own self-harm or suicidal intentions, behaviors, plans, or strong emotions.

 Example: "I really don't want to live anymore, I've even written a suicide note."

• 2: Third-party self-harm/suicide comments

- Posts only discussing others' self-harm/suicide situations, social news, seeking help, etc.
- Example: "My classmate was hospitalized for cutting her wrists due to depression, I don't know how to help her."

B.4 Common Issues and Handling Principles

B.4.1 Ambiguous/Vague Information

- If the post doesn't directly mention self or others but has slight implications with uncertain subjects, make reasonable inferences based on context. If unable to determine whether it refers to the author or others, it is recommended to mark as 1 (leaning toward the author's subtle disclosure) or temporarily retain as 0 (if insufficient evidence).
- If annotation functionality exists, add notes for clarification.

B.4.2 Jokes, Metaphors, or Rhetoric

- If the post appears to be joking or metaphorical, such as "I can't stop eating sweets, it's practically 'suicidal' sweet intake," and clearly not referring to actual suicide or ED, it should typically be marked as **0**.
- Context-based judgment is needed to determine if it's merely exaggerated expression.

B.4.3 Multiple Labels

- A post may simultaneously contain two or three self-harm tendencies. For example, if a post discusses both drug misuse and self-harm tendencies, mark "OD=1, SH=1". If ED is not mentioned, it remains 0.
- Evaluate each category's label independently, without mutual influence.

B.4.4 All Three Categories Marked as 0

• This means the post contains no text or implications related to OD, ED, or SH, in which case the post should be retained with labels (OD=0, ED=0, SH=0).

B.5 Annotation Format

- 1. Original post text or ID
- 2. OD annotation (0/1/2)
- 3. ED annotation (0/1/2)
- 4. SH annotation (0/1/2)
- 5. (Optional) Notes field: Brief explanation for ambiguous or controversial annotations.

B.6 Inter-annotator agreement

Table 4 presents the inter-annotator agreement metrics for the content annotation tasks related to drug overdose (OD), eating disorder (ED), and self-harm (SH). Two reliability measures are reported: Cohen's Kappa and Fleiss' Kappa, which are widely used to assess the agreement between annotators while accounting for chance agreement.

Cohen's Kappa measures pairwise agreement between two annotators or an annotator and an expert. Higher values indicate stronger agreement, with scores above 0.6 typically

interpreted as substantial agreement and scores above 0.8 as almost perfect agreement. In contrast, Fleiss' Kappa generalizes Cohen's Kappa to more than two annotators, providing an overall measure of agreement across all annotators.

For the overdose task (OD), the pairwise Cohen's Kappa scores range from 0.6434 (A2 vs. Expert) to 0.7491 (A1 vs. A2), with an average of 0.6917 and a Fleiss' Kappa of 0.6867. These values indicate substantial agreement among annotators for this task. The eating disorder task (ED) demonstrates higher reliability, with pairwise Cohen's Kappa scores ranging from 0.7089 to 0.8498, resulting in an average Kappa of 0.7820 and a Fleiss' Kappa of 0.7844. Similarly, the self-harm task (SH) achieves strong agreement, with pairwise Kappa values between 0.7122 and 0.8551, an average of 0.7785, and a Fleiss' Kappa of 0.7813.

Overall, the results suggest moderate to substantial inter-annotator agreement across all tasks, with the strongest reliability observed in the eating disorder task. This indicates that the annotation guidelines were consistently applied by the annotators, supported by their expertise and familiarity with the content. The use of both Cohen's and Fleiss' Kappa provides a comprehensive evaluation of agreement, capturing both pairwise and overall consistency.

Task	Pa	irwise Cohen's	Average	Fleiss' Kappa	
lask	A1 vs. A2	A1 vs. Expert	A2 vs. Expert	Average	Tielss Kappa
Overdose (OD)	0.7491	0.6826	0.6434	0.6917	0.6867
Eating Disorder (ED)	0.7089	0.8498	0.7872	0.7820	0.7844
Self-Harm (SH)	0.7122	0.8551	0.7681	0.7785	0.7813

Table 4: Inter-Annotator Agreement for Content Annotation Tasks

C Prompt

Table 5 illustrates the prompt templates designed for detecting self-destructive behavior across three languages—Chinese, Japanese, and English—and three behavior categories: OD, ED, and SH. These prompts are specifically crafted to leverage zero-shot and two-shot learning capabilities of LLMs, bypassing the need for traditional supervised training with labeled datasets.

Each prompt provides a clear and structured instruction to the LLM, ensuring that the model can classify social media content into one of three predefined categories:

- 1. 0: Content is completely unrelated to the specified behavior.
- 2. 1: Content implies or directly mentions the specified behavior.
- 3. 2: Content describes or comments on someone else's behavior within the specified category.

C.1 Zero-Shot and Two-Shot Use

These prompts are designed to take advantage of the zero-shot or two-shot capabilities of LLMs:

- 1. Zero-shot settings: The prompts provide all necessary context and instructions within a single input, enabling the LLM to perform the classification task without requiring any prior task-specific examples. For example, in the overdose (OD) category, the prompt instructs the LLM to determine whether the content relates to drug abuse and to return a single numerical label as the result.
- 2. Two-shot settings: In cases where a slight improvement in performance is desired, the prompts can be augmented with one or two labeled examples before presenting the actual content to classify. These examples illustrate the task expectations and help the LLM align its reasoning more closely with the intended outputs.

Type	Chinese	Japanese	English
OD	请判断以下社交媒体内容是 否涉及药物滥用。请只输出 一个数字作为结果: 0: 完全不相关 1: 暗示或直接提到药物滥	以下のソーシャルメディアの内容が薬物乱用に関連しているかどうかを判断してください。結果として数字のみを出力してください:	Determine if the following social media content is related to drug abuse. Please output only one number as the result:
	1: 暗示或直接提到约彻温用 用 2: 对他人药物滥用行为的 描述或评论	0:全く関連なし 1:薬物乱用を暗示または 直接言及 2:他人の薬物乱用行為の 描写またはコメント	0: Completely unrelated 1: Implies or directly mentions drug abuse 2: Description or comment on someone else's drug abuse behavior
ED	请判断以下社交媒体内容是 否涉及进食障碍。请只输出 一个数字作为结果: 0: 完全不相关 1: 暗示或直接提到进食障	以下のソーシャルメディアの内容が摂食障害に関連しているかどうかを判断してください。結果として数字のみを出力してください:	Determine if the following social media content is related to eating disorders. Please output only one number as the result:
	1: 唱小或直接提到近長障碍 碍 2: 对他人进食障碍行为的描述或评论	0:全く関連なし 1:摂食障害を暗示または 直接言及 2:他人の摂食障害行為の 描写またはコメント	0: Completely unrelated 1: Implies or directly mentions eating disorders 2: Description or comment on someone else's eating disorder behavior
SH	请判断以下社交媒体内容是否涉及自残或自杀倾向。请只输出一个数字作为结果: 0: 完全不相关 1: 暗示或直接提到自残/自杀	以下のソーシャルメディアの内容が自傷行為や自殺傾向に関連しているかどうかを判断してください。結果として数字のみを出力してください:	Determine if the following social media content is related to self-harm or suicidal tendencies. Please output only one number as the result:
	2: 对他人自残/自杀行为的描述或评论	0:全く関連なし 1:自傷/自殺を暗示または 直接言及 2:他人の自傷/自殺行為の 描写またはコメント	0: Completely unrelated 1: Implies or directly mentions self-harm/suicide 2: Description or comment on someone else's self-harm/suicide behavior

Table 5: Prompt templates used for self-destructive behavior detection across three languages (Chinese, Japanese, and English) and three categories: overdose (OD), eating disorders (ED), and self-harm (SH).

C.2 Multilingual and Multi-Category Design

The templates are standardized across Chinese, Japanese, and English to ensure consistency in task execution regardless of the language. This multilingual alignment allows the LLM to operate effectively across diverse linguistic contexts without retraining or fine-tuning. Similarly, the three categories (OD, ED, and SH) are designed with uniform label definitions to ensure interpretability and comparability across behaviors.

D JiraiLLM-Qwen

For our JiraiLLM-qwen model, we employed a conservative fine-tuning approach with carefully selected hyperparameters to balance computational efficiency and performance. The model was trained for 3 epochs on a high-performance computing infrastructure consisting of 4 NVIDIA A6000 GPUs, with a relatively small batch size of 5 supplemented by gradient accumulation steps of 10 (effectively creating a virtual batch size of 50) to optimize memory utilization while maintaining training stability. This hardware configuration provided suf-

ficient computational capacity to efficiently process our dataset of 3,000 Chinese samples while minimizing training time. All other hyperparameters were kept at their default values to maintain consistency with established fine-tuning protocols for the Qwen2.5 architecture.