Assessing Thai Dialect Performance in LLMs with Automatic Benchmarks and Human Evaluation

Peerat Limkonchotiwat[1,4,*], Kanruethai Masuk,[2,*], Surapon Nonesung[3,*],
Chalermpun Mai-On[2,*], Sarana Nutanong[2], Wuttikorn Ponwitayarat[2,*],
Potsawee Manakul[3,*],

[1]AI Singapore, [2]Vidyasirimedhi Institute of Science and Technology,
[3]SCB10X, [4]National University of Singapore,

Correspondence: peerat@aisingapore.org

Abstract

Large language models show promising results in various NLP tasks. Despite these successes, the robustness and consistency of LLMs in underrepresented languages remain largely unexplored, especially concerning local dialects. Existing benchmarks also focus on main dialects, neglecting LLMs' ability on local dialect texts. In this paper, we introduce a Thai local dialect benchmark covering Northern (Lanna), Northeastern (Isan), and Southern (Dambro) Thai, evaluating LLMs on five NLP tasks: summarization, question answering, translation, conversation, and food-related tasks. Furthermore, we propose a human evaluation guideline and metric for Thai local dialects to assess generation fluency and dialect-specific accuracy. Results show that LLM performance declines significantly in local Thai dialects compared to standard Thai, with only proprietary models like GPT-4o and Gemini2 demonstrating some fluency[1].

1 Introduction

Large language models (LLMs) play a crucial role in natural language processing (NLP) by significantly enhancing downstream performance across diverse tasks and languages. Studies have shown that LLMs surpass traditional multilingual models (Devlin et al., 2019; Conneau et al., 2020) in tasks such as question answering and summarization (Touvron et al., 2023; Pipatanakul et al., 2023). One key reason is that LLMs have significantly larger parameter counts and training datasets, often exceeding traditional models by a factor of 26, from 0.3 billion to 8 billion parameters. As a result, LLMs demonstrate greater robustness than traditional models across most scenarios, particularly in low-resource languages such as Thai (Pengpun et al., 2024; Phatthiyaphaibun et al., 2024),

Indonesian (Cahyawijaya et al., 2024, 2023), and Tagalog (Montalan et al., 2024; Gamboa and Lee, 2025).

Researchers are increasingly evaluating LLMs in underrepresented languages, particularly Thai, to assess their robustness and consistency in low-resource languages. Thai-H6 (Kim et al., 2025) introduces an evaluation benchmark for assessing LLMs' understanding of Thai cultural knowledge. SEACrowd (Lovenia et al., 2024) introduces a Southeast Asian benchmark for evaluating LLMs on local and cross-lingual texts, audios, and images, focusing on natural language generation and understanding. The Thai LLM benchmark[2] extends SEACrowd by incorporating LLM-as-a-Judge and Thai Exam datasets for a Thai language evaluation. However, these benchmarks primarily focus on the Central Thai dialect. Therefore, challenges observed in the Central dialect may also reflect underlying issues in local dialects.

Although there are 69 million Thai speakers, only about 20 million have Central Thai as their first language. The rest primarily grow up speaking other dialects, including approximately 15.2 million who speak Northeastern Thai (Isan), 6 million who speak Northern Thai (Lanna), and 4.5 million who speak Southern Thai (Dambro) or other local varieties. As shown in Figure 1a, a distinct feature of Thai local dialects is the blending of words between Central Thai and local dialects, as well as among different local dialects. Moreover, each local dialect has distinct words, some unique to that dialect and others shared with other dialects but not found in others. Recent studies examine the evaluation of fluency and understanding in local dialects of Indonesian (Syarfina et al., 2022; Cahyawijaya et al., 2023; Veria Septianingtias and Ariyani, 2024) and Filipino (Tabajunda, 2018; Gue-
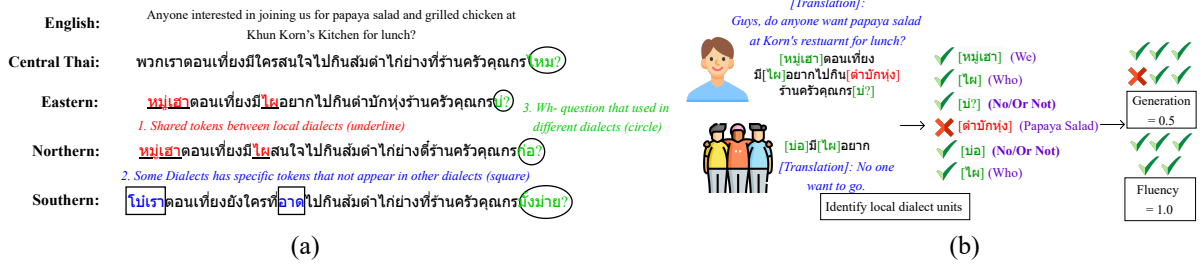

Figure 1: (a) We showed some unique characteristics of Thai local dialects compared to Central Thai: 1. shared tokens in local dialects; 2. unique words for each local dialect; and 3. WH- question tokens that are different in each local dialect. (b) Illustration of our local dialect evaluation metric. The example demonstrates the assessment of generation and fluency, highlighting variations in spelling and pronunciation among different Thai dialects.

vara et al., 2024). Evaluating the fluency and understanding of LLMs in Thai local dialects remains underexplored.

In this paper, we introduce a benchmark for evaluating local Thai dialects–Isan, Lanna, and Dambro–to assess LLMs' understanding of these dialects. Specifically, we evaluate LLMs on five tasks – summarization, question answering, translation, conversation, and food – using instructions, inputs, and labels written in local dialects. Additionally, we introduce human evaluation alongside a new *Thai local dialect guideline and metric* to assess LLMs' capabilities in understanding and generating local dialects. The new metric evaluates the generation and fluency of local dialects, rewarding or penalizing the model for fluency in a manner consistent with human speakers. Our experimental results show that LLM performance significantly declines on summarization and translation tasks when inputs are written in local dialects, compared to inputs in Central Thai. Furthermore, only proprietary models–GPT and Gemini–are capable of speaking local Thai dialects, as shown by both human evaluation and our new metric.

Our contributions are as follows: We introduce a benchmark for evaluating three Thai local dialects. We also propose a guideline and metric to assess the generation and fluency of LLMs in Thai local dialects. Lastly, we are the first to investigate Thai local dialects in the context of LLMs, presenting comprehensive evaluations using both traditional evaluation metrics and human assessment.

2 Benchmark and Metric

2.1 Benchmark Formulation

Data Selection. We create a new benchmark for evaluating three Thai local dialects–Isan, Lanna, and Dambro–drawing on examples from the Thai LLM leaderboard to assess model performance.

We select generation tasks—Question Answering (QA), summarization, and translation—because they are more complex and better suited for assessing model knowledge than more straightforward multiple-choice QA tasks. We randomly selected 20 samples for each task, resulting in 80 samples per dialect, where the translation task was both English to local dialects and vice versa. In addition, we include 10 topics on food (i.e., *asking for a food recipe of [FOOD_NAME]*) and conversations between two individuals discussing Thai traditional and cultural topics (i.e., *talking bout [TOPIC_NAME]*). The full topics can be found in Appendix A.7.

Gold Standard. Our dataset uses the gold standard provided by the original Central Thai examples. Note that we do not create labels for the food and conversation topics, as these tasks are open-ended and lack a definitive correct answer. Instead, we rely on human evaluation to assess these tasks. The number of samples is 100, all written in Central Thai.

Translation. We enlisted native speakers of each local dialect to translate the 100 samples from Central Thai into their respective dialects. This includes translating the input, context (for QA and summarization tasks), prompts, and labels, except for those related to food and conversation samples. Furthermore, all annotators are asked to review translations completed by their peers within the same region to ensure quality and consistency. Therefore, the total number of samples is 400, comparable to previous LLM-as-a-Judge and Human evaluation benchmarks (Zheng et al., 2023; Qin et al., 2024). For *the full information* of data statistics, prompts, topics, annotator demographics, and guidelines, see Appendix A.

Model	Dialect	QA	ΔDiff	Summarization	ΔDiff	Translation (E-L)	ΔDiff	Translation (L-E)	ΔDiff
Llama-3.1-8b	Central	60.74	-	20.07	-	11.41	-	44.61	-
Typhoon1.5-8b	Central	33.36	-	11.52	-	5.14	-	47.35	-
Llama-3.1-70b	Central	56.44	-	23.03	-	18.11	-	51.07	-
Typhoon1.5-70b	Central	46.99	-	10.83	-	8.46	-	50.54	-
GPT-4o	Central	56.03	-	14.67	-	21.926	-	62.82	-
Gemini2	Central	53.73	-	17.70	-	20.76	-	58.10	-
Llama-3.1-8b	Isan	58.84	1.90	16.47	3.60	3.17	8.24	6.59	38.02
Typhoon1.5-8b	Isan	28.48	4.88	8.54	2.98	0.83	4.31	31.6	15.75
Llama-3.1-70b	Isan	57.59	↑1.15	18.77	4.26	8.98	9.13	33.74	17.33
Typhoon1.5-70b	Isan	45.32	1.67	10.87	↑0.04	2.82	5.64	41.81	8.73
GPT-4o	Isan	44.21	11.82	10.39	4.28	14.29	7.63	55.26	7.56
Gemini2	Isan	40.58	13.15	12.68	5.02	13.31	7.45	51.74	6.36
Llama-3.1-8b	Lanna	55.66	5.08	18.05	2.02	2.46	8.95	7.27	37.34
Typhoon1.5-8b	Lanna	24.39	8.97	7.28	4.24	0.49	4.65	18.48	28.87
Llama-3.1-70b	Lanna	50.97	5.47	17.41	5.62	3.73	14.38	15.92	35.15
Typhoon1.5-70b	Lanna	44.74	2.25	10.17	0.66	4.76	3.70	39.01	11.53
GPT-4o	Lanna	45.73	10.30	9.78	4.89	12.02	9.90	54.83	7.99
Gemini2	Lanna	40.86	12.87	11.70	6.0	7.68	13.08	47.28	10.82
Llama-3.1-8b	Dambro	61.38	↑0.64	16.91	3.16	7.22	4.19	24.02	20.59
Typhoon1.5-8b	Dambro	31.34	2.02	9.18	2.34	4.20	0.94	27.81	19.54
Llama-3.1-70b	Dambro	66.96	↑10.52	17.2	5.83	7.66	10.45	27.10	23.97
Typhoon1.5-70b	Dambro	52.10	↑5.11	9.74	1.09	0.78	7.68	39.19	11.35
GPT-4o	Dambro	49.28	6.75	12.87	1.80	12.95	8.97	45.32	17.50
Gemini2	Dambro	47.91	5.82	12.07	5.63	9.13	11.63	23.46	34.64

Table 1: The main results of our benchmark. We calculate the ΔDiff by comparing Central and local dialects at the same model. In addition, E equals to English and L equals to local dialects.

2.2 Human Evaluation for Local Dialects

Traditional evaluation metrics, such as BLEU (Papineni et al., 2002) and ROUGE-L (Lin, 2004), struggle to assess dialectal text accurately. A key challenge is their reliance on tokenization, which fails when dialect words are missing from standard dictionaries, resulting in inaccurate segmentation. Furthermore, the absence of a standardized writing system leads to multiple valid spellings for the same word. Therefore, these traditional metrics that compare generated text to a fixed reference fail to account for such variations, often misclassifying correct responses as errors. These limitations underscore the urgency of developing more flexible evaluation methods that reflect the linguistic diversity of dialects.

To bridge these gaps, we conduct our local dialect evaluation metric as follows.

1. Annotators evaluate whether the generated output includes accurate local units, covering all forms of writing: nouns, phrases, and sentences.
2. Different dialect spellings are allowed if they share the same pronunciation. We ensure this by transliterating the word and comparing its phonetic transcriptions.
3. We divide our assessment into two categories: language *Generation* (similar to recall) and language *Fluency* (similar to precision). First, annotators (native local dialect speakers) evaluate language *Generation* by assigning a score of 0 (no local dialect generated), 0.5 (partially generated), or 1 (fully generated). Next, annotators

assess the correctness and naturalness (*Fluency*) of the generated dialectal words using the same scoring system as *Generation*: 0 (completely incorrect), 0.5 (partially correct), and 1 (fully correct and natural). The final score is calculated by the average over two annotators.

Figure 1(b) illustrates an example of our evaluation using the proposed metrics. Some extracted units have the same meaning but are written differently. Both writings are considered correct because they share the same pronunciation. In addition, the averages of annotator agreements (Appendix A.4) from three dialects are 0.7969 and 0.7449 for *Generation* and *Fluency*, respectively. We discussed the possibility of replacing humans with LLMs in Appendix B.

3 Experimental Setups and Results

3.1 Setup

To evaluate Thai local dialects, we use well-known Thai and multilingual LLMs for 8 and 70 billion parameters, namely Typhoon1.5 [3] and Llama3.1 [4]. We also evaluate proprietary LLMs, such as GPT-4o and Gemini2, in our benchmark. We use BLEU for translation and ROUGE-L for QA and summarization according to the original benchmark (Lovenia et al., 2024), including the generation setting for a fair comparison with previous benchmark works.

---

[3] https://huggingface.co/collections/scb10x/typhoon-15x-6648d7b07ab33d141d6648b6
[4] https://huggingface.co/collections/meta-llama/llama-31-669fc079a0c406a149a5738f

A vs B	Isan				Lanna				Dambro			
	A	B	Both	None	A	B	Both	None	A	B	Both	None
Typhoon1.5-8b vs Llama3.1-8b	1	-	-	19	-	-	-	20	1	-	-	19
Typhoon1.5-70b vs Llama3.1-70b	-	1	-	19	2	-	-	18	4	-	-	16
Gemini2 vs Typhoon1.5-70b	20	-	-	-	19	-	-	1	16	2	1	1
Gemini2 vs GPT-4o	4	3	13	-	18	-	2	-	16	2	2	-

Table 2: Human fluency preference on conversation and food topics. The full details are described in Section 3.3.

3.2 Traditional Metric Results

Table 1 shows a significant decline in translation performance for both 8B and 70B models, with the largest drop observed in Lanna. Results in Isan and Dambro were more mixed. In particular, QA performance improved in both Dambro and Isan. One possible explanation is that ROUGE-L measures only text overlap, assessing correctness based on matching words rather than fluency. Appendix C provides LLMs' outputs, revealing that ROUGE-L assigned high scores even when Llama-3.1-70B failed to produce local dialects. In particular, *none of the models produced responses in Thai local dialects*, even when explicitly prompted to do so. If reference labels are not written in local dialects, models may still achieve high scores despite failing to generate dialectal text, as shown in Table A.2 that QA and summarization exhibit higher word overlap in Central and local dialects than translation. This highlights the need for alternative evaluation techniques that assess fluency rather than relying solely on exact match metrics.

3.3 Human Evaluation

To verify that *existing models do not generate Thai local dialects* and *the traditional metric problem in Thai local dialects*, we conduct a human evaluation focused on fluency in food and conversation topics. We also recruit three native speakers per dialect to assess the fluency of LLM outputs, selecting one of four options: (A) for Prefer A, (B) for Prefer B, (Both) for liking both models equally, or (None) for disliking without any preference. In addition, we average the answer from three annotators to formulate the final answer. The annotator guideline can be found in Appendix A.6.

Table 2 confirms that all open-source models fail to generate Thai local dialects, as expected. Typhoon and Llama received the highest number of *both are the worst* ratings from annotators. For the Dambro dialect, Typhoon demonstrates some ability to generate local dialects, aligning with Table 1, where it showed improvement in Dambro texts. Gemini generates local dialects more fluently and outperforms other models in nearly every

comparison. However, these results reflect only a preference-based evaluation, while the actual fluency of LLMs in local dialects remains unmeasured. This underscores the need for an alternative metric to assess dialect fluency beyond exact match scores or subjective human ratings.

3.4 Our Local Dialect Metric

To better assess LLMs' fluency and generative ability in local dialects, we evaluate them using our proposed metric. As described in Section 2.2, two native speakers evaluate Typhoon1.5-70B and Gemini2 for QA, summarization, and translation.

Table 3 shows that when we focus only on evaluating the generation and fluency performance in Thai local dialects, only Gemini2 speaks Thai local dialects. Although Typhoon1.5-70b outperformed Gemini2 in the traditional metric performance in Table 1, we found a significant gap between these models. Gemini2 achieves over ∼92.58 points in the Lanna dialect and ∼84.49 points in Dambro, while Typhoon achieves less than 31 points and 12 points in Dambro and Lanna, respectively. Moreover, the results of our experiment also conform with Table 2 that Gemini2 is better than Typhoon1.5 with more deep analysis results, the Generation and Fluency score. This emphasizes the robustness of our metric, which can measure the ability to speak the local dialect fluently, unlike the traditional metrics (Table 1) and human preference (Table 2).

Model	Isan			Lanna			Dambro		
	G.	F.	Avg.	G.	F.	Avg.	G.	F.	Avg.
Typhoon	10.34	15.74	13.04	10.71	13.22	11.97	30.50	30.00	30.25
Gemini2	**86.57**	**82.41**	**84.49**	**91.33**	**93.99**	**92.58**	**75.50**	**68.50**	**71.83**

Table 3: The results from our propose metric. Note that G. is Generation and F. is Fluency.

4 Conclusion

Our study highlights the significant performance gap in LLMs when processing Thai local dialects. While proprietary models like GPT-4 and Gemini demonstrate some capability in understanding and generating local dialects, most LLMs struggle with fluency and accuracy. Our proposed benchmark, human evaluation, and a new guideline and met-

rics provide valuable insights into these limitations, paving the way for future improvements in multilingual and dialect-aware LLMs.

Limitation

- We select only the main local dialects in Thailand since some dialects do not have a writing system, only speaking.

- We experiment only with top-performance Thai LLMs, such as Typhoon1.5, Llama3.1, Gemini2, and GPT-4o. We acknowledge other Thai LLMs, such as WangchanLION and OpenThaiGPT. However, we found that only the typhoon model has 8 and 70 billion model parameters, covering all experiments in our paper.

- Extending the proposed metric to other languages. We acknowledge that our paper does not explain extending our metric to other languages. Our proposed metric can extend to other languages when human annotators who can speak local dialects are available. We will study this in our future work.

- Limited number of annotators. We use only five annotators for each local dialect. However, the agreement score demonstrated a high agreement in the annotation part.

Ethical Statement

All annotators are volunteers. In addition, we demonstrate the annotator details in Appendix A.3. Moreover, we will release our Thai local dialect and human evaluation results, for both the training and our human evaluation methods, to the public with the original license of each dataset, such as XL-SUM (Hasan et al., 2021) and iAPP (Viriyayudhakorn and Polpanumas, 2021). In addition, we have the dataset that was created by hand, and we will release it with license CC-BY-SA, similar to previous works.

Acknowledgement

References

Samuel Cahyawijaya, Holy Lovenia, Alham Fikri Aji, Genta Winata, Bryan Wilie, Fajri Koto, Rahmad Mahendra, Christian Wibisono, Ade Romadhony, Karissa Vincentio, Jennifer Santoso, David Moeljadi, Cahya Wirawan, Frederikus Hudi, Muhammad Satrio Wicaksono, Ivan Parmonangan, Ika Alfina, Ilham Firdausi Putra, Samsul Rahmadani, Yulianti Oenang, Ali Septiandri, James Jaya, Kaustubh Dhole, Arie Suryani, Rifki Afina Putri, Dan Su, Keith Stevens, Made Nindyatama Nityasya, Muhammad Adilazuarda, Ryan Hadiwijaya, Ryandito Diandaru, Tiezheng Yu, Vito Ghifari, Wenliang Dai, Yan Xu, Dyah Damapuspita, Haryo Wibowo, Cuk Tho, Ichwanul Karo Karo, Tirana Fatyanosa, Ziwei Ji, Graham Neubig, Timothy Baldwin, Sebastian Ruder, Pascale Fung, Herry Sujaini, Sakriani Sakti, and Ayu Purwarianti. 2023. NusaCrowd: Open source initiative for Indonesian NLP resources. In *Findings of the Association for Computational Linguistics: ACL 2023*, pages 13745–13818, Toronto, Canada. Association for Computational Linguistics.

Samuel Cahyawijaya, Holy Lovenia, Fajri Koto, Rifki Putri, Wawan Cenggoro, Jhonson Lee, Salsabil Akbar, Emmanuel Dave, Nuurshadieq Nuurshadieq, Muhammad Mahendra, Rr Putri, Bryan Wilie, Genta Winata, Alham Aji, Ayu Purwarianti, and Pascale Fung. 2024. Cendol: Open instruction-tuned generative large language models for Indonesian languages. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 14899–14914, Bangkok, Thailand. Association for Computational Linguistics.

Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2020. Unsupervised cross-lingual representation learning at scale. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 8440–8451, Online. Association for Computational Linguistics.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Lance Calvin Lim Gamboa and Mark Lee. 2025. Filipino benchmarks for measuring sexist and homophobic bias in multilingual language models from Southeast Asia. In *Proceedings of the First Workshop*

on Language Models for Low-Resource Languages, pages 123–134, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

Rowena Cristina L. Guevara, Rhandley D. Cajote, Michael Gringo Angelo R. Bayona, and Crisron Rudolf G. Lucas. 2024. Philippine languages database: A multilingual speech corpora for developing systems for low-resource languages. In *Proceedings of the 3rd Annual Meeting of the Special Interest Group on Under-resourced Languages @ LREC-COLING 2024*, pages 264–271, Torino, Italia. ELRA and ICCL.

Tahmid Hasan, Abhik Bhattacharjee, Md. Saiful Islam, Kazi Mubasshir, Yuan-Fang Li, Yong-Bin Kang, M. Sohel Rahman, and Rifat Shahriyar. 2021. XL-sum: Large-scale multilingual abstractive summarization for 44 languages. In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pages 4693–4703, Online. Association for Computational Linguistics.

Dahyun Kim, Sukyung Lee, Yungi Kim, Attapol Rutherford, and Chanjun Park. 2025. Representing the under-represented: Cultural and core capability benchmarks for developing Thai large language models. In *Proceedings of the 31st International Conference on Computational Linguistics*, pages 4114–4129, Abu Dhabi, UAE. Association for Computational Linguistics.

Chin-Yew Lin. 2004. ROUGE: A package for automatic evaluation of summaries. In *Text Summarization Branches Out*, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.

Holy Lovenia, Rahmad Mahendra, Salsabil Maulana Akbar, Lester James Validad Miranda, Jennifer Santoso, Elyanah Aco, Akhdan Fadhilah, Jonibek Mansurov, Joseph Marvin Imperial, Onno P. Kampman, Joel Ruben Antony Moniz, Muhammad Ravi Shulthan Habibi, Frederikus Hudi, Jann Railey Montalan, Ryan Ignatius Hadiwijaya, Joanito Agili Lopo, William Nixon, Börje F. Karlsson, James Jaya, Ryandito Diandaru, Yuze Gao, Patrick Amadeus Irawan, Bin Wang, Jan Christian Blaise Cruz, Chenxi Whitehouse, Ivan Halim Parmonangan, Maria Khelli, Wenyu Zhang, Lucky Susanto, Reynard Adha Ryanda, Sonny Lazuardi Hermawan, Dan John Velasco, Muhammad Dehan Al Kautsar, Willy Fitra Hendria, Yasmin Moslem, Noah Flynn, Muhammad Farid Adilazuarda, Haochen Li, Johanes Lee, R. Damanhuri, Shuo Sun, Muhammad Reza Qorib, Amirbek Djanibekov, Wei Qi Leong, Quyet V. Do, Niklas Muennighoff, Tanrada Pansuwan, Ilham Firdausi Putra, Yan Xu, Tai Ngee Chia, Ayu Purwarianti, Sebastian Ruder, William Chandra Tjhi, Peerat Limkonchotiwat, Alham Fikri Aji, Sedrick Keh, Genta Indra Winata, Ruochen Zhang, Fajri Koto, Zheng Xin Yong, and Samuel Cahyawijaya. 2024. SEACrowd: A multilingual multimodal data hub and benchmark suite for Southeast Asian languages. In *Proceedings of*

the 2024 Conference on Empirical Methods in Natural Language Processing, pages 5155–5203, Miami, Florida, USA. Association for Computational Linguistics.

Jann Railey Montalan, Jian Gang Ngui, Wei Qi Leong, Yosephine Susanto, Hamsawardhini Rengarajan, Alham Fikri Aji, and William Chandra Tjhi. 2024. Kalahi: A handcrafted, grassroots cultural llm evaluation suite for filipino. *Preprint*, arXiv:2409.15380.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*, pages 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.

Parinthapat Pengpun, Can Udomcharoenchaikit, Weerayut Buaphet, and Peerat Limkonchotiwat. 2024. Seed-free synthetic data generation framework for instruction-tuning llms: A case study in thai. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics, ACL 2024 - Student Research Workshop, Bangkok, Thailand, August 11-16, 2024*, pages 438–457. Association for Computational Linguistics.

Wannaphong Phatthiyaphaibun, Surapon Nonesung, Peerat Limkonchotiwat, Can Udomcharoenchaikit, Jitkapat Sawatphol, Ekapol Chuangsuwanich, and Sarana Nutanong. 2024. CHIE: Generative MRC evaluation for in-context QA with correctness, helpfulness, irrelevancy, and extraneousness aspects. In *Proceedings of the 2nd GenBench Workshop on Generalisation (Benchmarking) in NLP*, pages 154–164, Miami, Florida, USA. Association for Computational Linguistics.

Kunat Pipatanakul, Phatrasek Jirabovonvisut, Potsawee Manakul, Sittipong Sripaisarnmongkol, Ruangsak Patomwong, Pathomporn Chokchainant, and Kasima Tharnpipitchai. 2023. Typhoon: Thai large language models. *Preprint*, arXiv:2312.13951.

Yiwei Qin, Kaiqiang Song, Yebowen Hu, Wenlin Yao, Sangwoo Cho, Xiaoyang Wang, Xuansheng Wu, Fei Liu, Pengfei Liu, and Dong Yu. 2024. InFoBench: Evaluating instruction following ability in large language models. In *Findings of the Association for Computational Linguistics: ACL 2024*, pages 13025–13048, Bangkok, Thailand. Association for Computational Linguistics.

Tengku Syarfina, Satwiko Budiono, and Denny Adrian Nurhuda. 2022. Language variations in jayapura city: A study of dialectology. EAI.

Dastin Tabajunda. 2018. Linguistic schoolscape as public communication: A study of announcements and signages in de la salle university – dasmariñas. In *Proceedings of the 32nd Pacific Asia Conference on Language, Information and Computation*, Hong Kong. Association for Computational Linguistics.

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. 2023. Llama: Open and efficient foundation language models. *Preprint*, arXiv:2302.13971.

Tajudin Nur Veria Septianingtias, Wahya and Farida Ariyani. 2024. Lexical variation in the lampung language, indonesia. *Cogent Arts & Humanities*, 11(1):2309740.

Kobkrit Viriyayudhakorn and Charin Polpanumas. 2021. iapp_wiki_qa_squad.

Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric Xing, Hao Zhang, Joseph E. Gonzalez, and Ion Stoica. 2023. Judging LLM-as-a-judge with MT-bench and chatbot arena. In *Thirty-seventh Conference on Neural Information Processing Systems Datasets and Benchmarks Track*.

A Data Statistics and Annotators

A.1 Data Statistics

As shown in Table 4, we have a total of 100 samples for each local dialect. We use summarization, QA, and translation for the traditional metric, BLEU, and ROUGE-L. In contrast, we use conversation and food topics for human evaluation since these topics do not have the perfect answer, as in previous tasks. In addition, the topics of food and conversation are culturally relevant, such as local food in Southern or Northern Thailand, and the conversation topic is events and culture in each part of Thailand. In addition, we have 40 samples for translation since it is forward and backward translation. Moreover, the QA samples are from iAPP (Viriyayudhakorn and Polpanumas, 2021), the summarization samples are from XL-SUM (Hasan et al., 2021), and the translation, food, and conversation samples are formulated by annotators.

Dialects	#Sample of Summarization	#Sample of QA	#Sample of Transaltion	#Sample of Conversation	#Sample of Food
Isan	20	20	40	10	10
Lanna	20	20	40	10	10
Dambro	20	20	40	10	10

Table 4: Data Statistical: Number of Samples

A.2 Word Overlap

As shown in Table 5, we observe that the translation had the least overlap compared to other tasks. This conforms with the results in Table 1 that the least word overlap yields the lowest penalty, directly affecting the downstream task performance.

However, the word-overlap score still cannot explain the fluency performance of LLMs in speaking Thai local dialects.

Dialects	Summarization	QA	Translation
Isan	0.9628	0.9167	0.9067
Lanna	0.9767	0.93318	0.9072
Dambro	0.9598	0.9008	0.9036

Table 5: Data Statistical: Word Overlap

A.3 Annotators

We list the author's biographic as follows. For Lanna, we have two women and three men, and annotators are between 25 and 30 years old. For Isan, we have three women and two men; the annotators are between 25 and 30 years old and 31 and 35 years old. For Dambro, we have three women and two men, and annotators are between 25 and 30 years old. All annotators are born in non-Central Thailand and speak local and Central dialects.

A.4 Annotator Agreement

In this study, we calculate the annotator agreement of our proposed metric using Cohen's Kappa score. We use two annotators in this experiment, and both of them need to annotate the same sample (100% sample overlap). As shown in Table 6, we found that Isan and Dambro have a similar agreement score, 0.7 points, with a substantial agreement. Moreover, we found almost perfect agreement on Lanna. This is because the model can speak Lanna better than other dialects. When the annotators assign the score, it is easier for them to judge it.

Agreement	Lanna		Isan		Dambro	
	Generation	Fluency	Generation	Fluency	Generation	Fluency
Cohen_kappa	0.9315	0.7319	0.7078	0.7077	0.7514	0.7951

Table 6: Data Statistical: Annotator agreement of our proposed metric.

A.5 Example Code

Since we use all the generation setup from Lovenia et al. (2024), we can run all the experiments with one line code, similar to SEACrowd. For example:

```bash
#!/bin/bash
MODEL_NAME='meta-llama/Llama-3.1-8B-
    Instruct'
python evaluation/
    main_local_prompt_batch.py south ${
    MODEL_NAME} 0 1
python evaluation/
    main_local_prompt_batch.py north ${
    MODEL_NAME} 0 1
```

Listing 1: Example Code

In addition, the output will be in the CSV format, including scores according to tasks. The benchmark can be run on a single A100 or H100 (800 GB) within < 1 hour.

A.6 Guideline for Annotators

Translation. From Section 3.2, we translate from Central Thai to Thai local dialects using the following guideline:

> Translation Task
>
> In this task, we need your help to revise the translation of the prompt and its response from English to your native language.
>
> Comparing Original and translated texts and then editing the translation to be more human (write your revision in the edit column)
>
> The goal is to make the translation results look more like human writing
>
> Note that the edit columns can't be null. You need to edit all the translations.
>
> Do not remove or edit emojis, hashtags, or special characters If the text represents gender (she/he), please change it to the general context (I, you, they, them)
>
> All texts should be edited since it is not 100% natural. There is no empty field in the revision column.

Model Comparison Guideline. From Section 3.3, we ask three annotators to compare model A vs. B where we mean the answer to get the final answer of each sample. Annotators are blinded to model identities for all examples. In addition, we average the answer from three annotators into the final answer.

> Guidelines for Evaluating Model A and Model B
>
> Evaluation Objective: Assess the performance of Model A compared to Model B in responding to provided questions/instructions/prompts.
>
> Evaluate based on the following two aspects: 1. Accuracy of local dialect/language usage 2. Accuracy of the response
>
> Evaluation Options: You must choose only one option for each criterion:

> (i) A is better than B: Model A performs better than Model B in the given aspect
>
> (ii) B is better than A: Model B performs better than Model A in the given aspect
>
> (iii) A and B are equally good: Both models perform equally well in the given aspect
>
> (iv) A and B are equally poor: Both models perform equally poorly in the given aspect
>
> Evaluation Justification: Provide a short reason explaining why you chose that score (repeating reasons is allowed if the outputs are similar).

A.7 Food and Conversation Topics

We provide the full food and conversation topics in Figure 2.

A.8 Prompts

We demonstrate the prompt we used in our experiment in Figure 3. Note that all prompts are written in local dialects, and we also added instructions for performing in local dialects.

B LLM-as-a-judge

We acknowledge that the limitation of our proposed metric is relying on human 100%. We use native speakers to judge the fluency and generation score for LLMs' output. However, we tried to use LLM-as-a-judge to solve this problem and found that LLMs (i.e., Gemini2 and GPT4o) are not good enough to understand Thai local dialects fluency, resulting in inaccurate judgment compared to native speakers. Although Gemini2 achieves a high score in Table 3, when it acts like a judge, it fails to give a similar fluency score to the human, where the preliminary results show that the correlation between Geimini2 and Humans on Lanna is only 53.6 points (Spearman's correlation). Therefore, we omit the LLM-as-a-judge from our work.

C Output Examples

In this study, we show the incorrect and correct examples when we focus on the local dialect output. We divided it into two categories: (i) answer correctly with no local dialects, and (ii) answer correctly with local dialects to make it easier to understand local Thai dialects. Note that we use the output from Typhoon1.5-70b and Gemini2.

Food			Conversation
Isan	**Lanna**	**Dambro**	
แจ่วบักเขือ	ลาบเหนือ	แกงพุงปลา	ประเพณีท้องถิ่น
อ่อมน่องวัว	ขนมจีนน้ำเงี้ยว	แกงส้ม	อาชีพ
ตำบักหุ่ง	แกงฮังเล	ลอกอผัดไข่	การคมนาคม
หมกหน่อไม้	น้ำพริกหนุ่ม	ข้าวผัดเคย	ครอบครัว
ซอยจุ๊	น้ำพริกอ่อง	แกงส้มปลาพงยอดพร้าว	กลับบ้านช่วงเทศกาล
แกงขี้เหล็ก	แกงหัวปลี	ข้าวผัดเคย	การเมืองท้องถิ่น
น้ำตกคอหมูย่าง	แกงหยวก	ปลาซายท้อดขี้มิ้น	สภาพอากาศ
ปลาส้ม	ไส้อั่ว	ผัดผักเหลี่ยง	อาหารท้องถิ่น
แจ่วฮ้อน	แคบหมู	แก่งเลียง	เครื่องแต่งกายท้องถิ่น
ตับหวาน	แกงกระด้าง	ผัดหลูกต่อ	การศึกษาท้องถิ่น

Figure 2: Food and Conversation topics. Note that these food names are very local in each part of Thailand.

Figure 3: The Thai prompts that we used in our experiments with the translation version.

Figure 4: Example from the translation task.

As shown in Figure 4, we notice that while Ty-phoon can translate the text correctly, there are no local dialects in this case. In contrast, Gemini2 (anotator prefer) can translate from English to local dialect correctly. Moreover, we also observe Fig-ure that both models code-switch between Central and local dialects, as underscored in Figure 1. This suggests that the gap in making LLMs speak Thai

local dialects is significantly broad and needs more
attention.