NitiBench: Benchmarking LLM Frameworks on Thai Legal Question Answering Capabilities

Pawitsapak Akarajaradwong[†1], **Pirat Pothavorn**[†1], **Chompakorn Chaksangchaichot**[†1],
Panuthep Tasawong[2], **Thitiwat Nopparatbundit**[1], **Keerakiat Pratai**[3], **Sarana Nutanong**[2]
[1]VISAI AI [2]Vidyasirimedhi Institute of Science and Technology [3]Thammasat University
{pawitsapaka_visai,piratp_visai,chompakornc_pro,thitiwatn_visai}@vistec.ac.th
{panuthep.t_s20,sarana.n}@vistec.ac.th
pratai@tu.ac.th
† These authors contributed equally to this work

Abstract

Large language models (LLMs) show promise in legal question answering (QA), yet Thai legal QA systems face challenges due to limited data and complex legal structures. We introduce NitiBench, a novel benchmark featuring two datasets: (1) NitiBench-CCL , covering Thai financial laws, and (2) NitiBench-Tax , containing Thailand's official tax rulings. Our benchmark also consists of specialized evaluation metrics suited for Thai legal QA. We evaluate retrieval-augmented generation (RAG) and long-context LLM (LCLM) approaches across three key dimensions: (1) the benefits of domain-specific techniques like hierarchy-aware chunking and cross-referencing, (2) comparative performance of RAG components, e.g., retrievers and LLMs, and (3) the potential of long-context LLMs to replace traditional RAG systems. Our results reveal that domain-specific components slightly improve over naive methods. At the same time, existing retrieval models still struggle with complex legal queries, and long-context LLMs have limitations in consistent legal reasoning. Our study highlights current limitations in Thai legal NLP and lays a foundation for future research in this emerging domain.

1 Introduction

Large language models (LLMs) are rapidly transforming legal research and question answering (QA), chiefly via Retrieval-Augmented Generation (RAG) pipelines (LexisNexis, 2023; Strumberger, 2023; Takyar, 2024; ailawyer, 2025; asklegal.bot, 2024). Despite advancements in English legal QA, pipelines and benchmarks remain limited for resource-constrained languages like Thai. The flagship Thai service *Thanoy* (Viriyayudhakorn, 2024) operates via Line messenger, whose strict API rate limits hinder large-scale evaluation. Thanoy also cites statutes inconsistently, sometimes entire acts, sometimes individual sections, obstructing reliable retrieval evaluation. Thus, Thai legal QA faces bottlenecks in reliable statutory retrieval and the lack of standardized end-to-end (E2E) benchmarks.

Our work proposed **NitiBench** which fills this gap with two Thai legal-QA datasets plus section-level retrieval and E2E evaluation metrics focusing on the Corporate and Commercial Law (CCL) and Tax Law domain. We selected these two legal domains due to their structural complexity and practical relevance. For example, the Civil and Commercial Code contains more than 1,700 sections, the most among Thai legislation, while the Revenue Code has its own unique hierarchical structure. These datasets are manually reviewed to ensure the highest reliability and serve as difficult representations of Thai legal texts. CCL and Tax Law require reasoning over interrelated sections, making them ideal for evaluating RAG systems and long-context LLMs. They also address everyday issues like contracts, property, and taxation, offering both technical depth and practical relevance.

We further use our benchmark to examine limitations in today's LLM frameworks, such as RAG and Long Context Language Models (LCLMs). Our results reveal limitations in existing retrievers and LLMs for complex legal reasoning, particularly with the NitiBench-Tax dataset. Our benchmark and findings aim to facilitate systematic progress in Thai legal NLP.

Our key contributions include:

- **Two Thai QA Dataset for Legal QA**[1]: *NitiBench-CCL Dataset* covers general financial law, while the *NitiBench-Tax Dataset* specifically focuses on complex tax cases. Each query includes a question, answer, and relevant documents for detailed retrieval and E2E evaluation. We named our benchmark, which consists of two datasets and proposed metrics (shown in §3.2), as **NitiBench**.

[1] https://huggingface.co/datasets/VISAI-AI/nitibench

Proceedings of the 2025 Conference on Empirical Methods in Natural Language Processing, pages 34304–34327
November 4-9, 2025 ©2025 Association for Computational Linguistics

- **Tailored Metrics for Thai Legal QA**: We propose multi-label retrieval metrics and E2E metrics that assess accuracy, consistency, and legal citation quality.
- **Comprehensive Analysis**: By combining the datasets constructed through our pipeline with evaluations based on our proposed metrics, we aim to address three key research questions: **(RQ1)** How can chunking strategies that are tailored to the hierarchical nature of the Thai legal system and a section[2] referencing component improve performance? **(RQ2)** How do retriever and LLM choices impact RAG performance? **(RQ3)** How do long-context LLM (LCLM) based Thai legal QA systems perform compared to RAG-based approaches? To the best of our knowledge, the insights from these research questions, particularly the interaction between legal document structure and model performance, have not been previously explored due to the lack of suitable datasets and standardized evaluation methodologies.

2 Related Work

Legal QA Benchmarks. Benchmarking legal QA systems is crucial for standardized evaluation. Existing English benchmarks such as LexGlue (Chalkidis et al., 2022), LegalBench (Guha et al., 2023), and LegalBench-RAG (Pipitone and Alami, 2024) address various subtasks (e.g., court opinion classification, contract NLI, retrieval), but often fall short in evaluating end-to-end open-question-answering performance of RAG systems. Recent works (Dahl et al., 2024; Magesh et al., 2024; Es et al., 2023) introduce multiple aspects for evaluating open-domain QA tasks in retrieval-augmented generation (RAG), with a strong emphasis on faithfulness, groundedness, and relevance of the generated answers. As for the retrieval evaluation, to the best of our knowledge, no prior work has developed multi-label variants of traditional retrieval metrics (such as hit rate, MRR, and recall), which are inadequate for capturing the inherent multi-label nature of the legal reasoning process.

RAG in Legal Practice. RAG approaches enhance LLM outputs by incorporating relevant legal texts (Lewis et al., 2021; Wiratunga et al., 2024). Despite promising applications in commercial systems like Lexis+ AI (LexisNexis, 2023), Westlaw (Strumberger, 2023), and Thanoy (Viriyayudhakorn, 2024), hallucination and retrieval accuracy remain problematic (Magesh et al., 2024).

RAG vs Long-Context LLMs. An alternative, Long-Context LLMs (LCLMs), can process extended texts without separate retrieval (Laban et al., 2024; Lee et al., 2024b; Reid et al., 2024). However, while LCLMs offer advantages in context length, studies have found them less effective than RAG for tasks requiring precise citation and comprehensive coverage (Kamradt, 2023; Bai et al., 2024; An et al., 2023; Lee et al., 2024b; Li et al., 2024; Phan et al., 2024), especially in the legal domain. Our work directly compares RAG and LCLM approaches for Thai legal QA, addressing this important gap.

3 Methodology

In §3, we outline **NitiBench** comprising two datasets: **NitiBench-CCL** and **NitiBench-Tax** . We also cover the evaluation framework of NitiBench for Thai legal QA systems, addressing retrieval and end-to-end (E2E) performance.

Formally, given the set of sections L extracted from NitiBench-CCL , both formats can be represented as $\mathcal{D} = \{(\mathbf{x}_1, y_1), ..., (\mathbf{x}_N, y_N)\}$, where $\mathbf{x}_i = (q_i, T_i \subset L)$ - q_i denotes query or question, T_i is a set of positive documents (sections) corresponded to q_i. The label y_i is the free-form text answer to question q_i given the context T_i.

3.1 Datasets

NitiBench-CCL (**C**orporate and **C**ommercial **L**aw) is a Thai financial law QA dataset with 35 pieces of legislation, including a test set for evaluation. NitiBench-CCL was derived from WangchanX-Legal-ThaiCCL-RAG's test set with an additional postprocessing step where we utilize an LLM to extract only the essential answers without the accompanying rationale.We note that the intuition behinds removal of rationale are two folds: 1) Simplifying LM-based evaluation as it reduce complexity for the judge potentially making judge task simpler 2) Token efficiency as rationale can sometimes be very long which could consume too much tokens for the judge LM. Nevertheless, our released dataset also contains the answer for two versions, including answer with and without ratio-

[2] In this paper, "section" refers to a component in legislation, while we use "§" to denote a section, subsection, or subsubsection in this document. For more information on Thai legal terminology, see Appendix G.

nale for flexible usage. The test set only contains a subset of 21 out of 35 pieces of legislation. These legislation are then parsed into sections, resulting in L.

For training data, we use original WangchanX-Legal-ThaiCCL-RAG[3] training set which contains multiple positives (See Appendix A for details on WangchanX-Legal-ThaiCCL-RAG data curation). Note that the test set contains only single positives. Details on NitiBench-CCL data curation, statistics, and examples can be found in Appendix B, D, and E.1, respectively.

To minimize domain shift, the same team of legal experts curated the entire dataset (see Appendix A.3 for details on the annotator profiles). They both refined the semi-synthetic training data and authored the fully human-annotated test set, ensuring consistent standards for question style and answer precision across both splits. This unified oversight validates the test set as a reliable benchmark for generalization

NitiBench-Tax is a specialized dataset for Thai tax rulings. It includes 50 cases from 2021-2024, with questions, answers, and referenced sections scraped from the Revenue Department of Thailand's website[4]. This dataset only contains a test set and is multi-labeled ($|T_i| \geq 1$). We also filtered any relevant section to ensure that the law cited in this dataset matches the set L used in NitiBench-CCL as well. For additional information on the NitiBench-Tax data curation process, statistics, and examples, refer to Appendix C, D, E.3, respectively.

3.2 Metrics

3.2.1 Retriever Metrics

We adapt traditional retrieval metrics for multi-label scenarios suitable for multi-label setup in our benchmark. Formally, let N be the number of samples in a dataset, k denote the number of top retrieved documents being evaluated, T_i represent the set of positive relevant documents, and R_i^k denote the top-k ranked retrieved documents.

HitRate@k. Measures if any relevant document is retrieved can be defined as:

$$\text{HitRate@k} = \frac{1}{N}\sum_{i=1}^{N}\mathbb{I}(R_i^k \subseteq T_i) \tag{1}$$

Multi-HitRate@k. Requires **all** relevant documents to be retrieved and is defined as:

$$\text{Multi-HitRate@k} = \frac{1}{N}\sum_{i=1}^{N}\mathbb{I}(T_i \subseteq R_i^k) \tag{2}$$

This can be view as a hard assignment for the HitRate under multi positives setup. This aligns with many legal use cases where any false negatives (missed legal sections) are critical on legal application as it can potentially lead to flawed legal reasoning under incomplete legal context.

Recall@k. Evaluates the proportion of relevant documents retrieved defined as:

$$\text{Recall@k} = \frac{1}{N}\frac{\sum_{i=1}^{N}|T_i \cap R_i^k|}{\sum_{i=1}^{N}|T_i|} \tag{3}$$

Recall@k is conceptually similar to R-Precision (Manning et al., 2008), in that R-Precision $=$ Recall@$|T_i|$. However, since the downstream application requires a fixed number of retrieved items k, which does not necessarily equal $|T_i|$, we opted to use Recall@k instead of R-Precision.

MRR@k. Assess ranking quality defined by:

$$\text{MRR@k} = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{\text{argmax}(T_i \cap R_i^k)} \tag{4}$$

where $\text{argmax}(T_i \cap R_i^k)$ represents the highest rank number of correctly retrieved documents. The metric is zero if $|T_i \cap R_i^k| = 0$ (retrieved document contains no positive).

MultiMRR@k. Traditional MRR is calculated under the assumption that any of the documents in the ground truth set T is considered a positive label (Zhan et al., 2020; Khattab and Zaharia, 2020). However, this assumption is not true, especially in a legal domain where, sometimes, all relevant laws must be retrieved for the system to be able to answer the question. Therefore, the equation 4 is augmented to MultiMRR as follows:

$$\begin{aligned}\text{MultiMRR@k} = \frac{1}{N}\sum_{i=1}^{N}\Bigg[\frac{\text{Recall@k}_i}{|T_i \cap R_i^k|} \\ \times \sum_{j=1}^{|T_i \cap R_i^k|}\frac{1}{\text{rank}(d_j) - j + 1}\Bigg].\end{aligned} \tag{5}$$

Intuitively, MultiMRR extends MRR under multi positives setup while also discounted ranks taking into account of multiple positives. In other words, this metrics encourage all relevant law sections to be appeared on the top rank.

[3] https://huggingface.co/datasets/airesearch/WangchanX-Legal-ThaiCCL-RAG

[4] https://www.rd.go.th

3.2.2 End-to-End Metrics

We design three complementary metrics to assess end-to-end answer quality and legal grounding:

Coverage. Following (Laban et al., 2024); the coverage score measures the semantic alignment between generated and ground truth answers via a 3-point scale:

- 100: Full coverage (all key points in ground truth addressed)
- 50: Partial coverage ($\geq$1 key point missing)
- 0: No meaningful overlap

Citation. Evaluating precision, recall, and F1 for cited sections following (Kamradt, 2023).

Contradiction. Quantifying hallucination by comparing generated answers to ground truth as a binary (1=contradiction, 0=consistent).

Both citation and contradiction scores are computed using LLM-as-a-judge, where we use `gpt-4o-2024-08-06` (Hurst et al., 2024) as a judge model with a temperature of 0.3. We also tune our prompt to ensure that the judge LLM achieves a high agreement with humans. The details on judge LLM performance are outlined in Appendix F.

4 Experimental Setups

In §4, we outline our experimental setup using our proposed benchmark to address three key research questions.

The LLM prompts are provided with 3-shot examples randomly sampled from the training data. All experiments were conducted on a single DGX A100 node (40GB, 4 GPUs) for both retriever finetuning and LLM inference.

4.1 (RQ1) Impact of Tailored Components

For this research question, we aim to address the impact of injecting domain knowledge towards two components in RAG: text chunking and prompt augmenting. We investigate the impact of modifying these two components to better suit domain knowledge and evaluate their effectiveness.

Hierarchy-aware Chunking. We propose a chunking strategy that preserves components in legislation as a hierarchical data structure via extensive regular expression and custom rule-based. We select only section-level nodes for experiments, as suggested in Appendix G. We compared our proposed Hierarchy-aware Chunking with a naive chunking strategy (see Appendix H on how we obtain naive chunking setups).

Since the naive chunking strategy has no awareness of section boundaries, the chunked text might either contain multiple sections (if the section is shorter than the chunk size) or be incomplete (if the section is longer than the chunk size). This makes it hard to justify whether a retrieved incomplete chunk (partially containing section content) is considered a correctly retrieved document. To simply retrieve and enable a fair comparison of top-k retrieval across strategies, **chunks that do not fully cover at least one section are discarded**. We also remove sections from the hierarchy-aware chunks that are not covered by the naive chunking strategy.

After filtering out sections that are not contained in the naive chunks, only 19 NitiBench-Tax entries and 2,625 NitiBench-CCL entries were left. Given the limited size of the NitiBench-Tax subset, we perform evaluations solely on NitiBench-CCL .

For this setup, we use a three-headed, Human-Finetuned BGE-M3 as a retriever (see § 4.2.1) and `gpt-4o` as the LLM.

The evaluation method based on naive chunking has inherent limitations, particularly in handling and evaluating partial sections, an area that remains an open research question. In this work, we acknowledge this constraint as a trade-off: while naive chunking simplifies implementation, it introduces complexity into the evaluation process.

NitiLink. To handle inter-section references, we introduce **NitiLink**, a framework that recursively fetches referenced sections and incorporates them into the LLM context. We adopt a depth-first referencing strategy where the referenced section will be placed next to the referencing section. For example, if Section A references Section B, NitiLink retrieves Section B and places it at the next rank after Section A. We evaluate its impact on retrieval and E2E performance using hierarchy-aware Chunking, Human-Finetuned BGE-M3 (see §4.2.1), and GPT-4o. We compare the performance of the RAG with and without NitiLink component using our proposed benchmark. We use a maximum reference depth of 1 due to a significant inference budget required since more reference depth increases prompt length dramatically.

4.2 (RQ2) Impact of Retriever and LLM

This research question aims to investigate the performance of two main components in the RAG system: Retrieval model and LLM. For each component, we conduct an experiment to compare the performance of the baseline ("naive RAG"), our "proposed RAG framework", and RAG with golden context which acts as an upper bound performance.

4.2.1 Retriever Models

Conventionally, BGE-M3 (Chen et al., 2024) was a popular choice for text embeddings due to its superior performance across languages and models. However, in some cases, BGE-M3 was also finetuned towards domain-specific data to improve the performance. Therefore, for this experiment, using our benchmark, we evaluate the effectiveness of the following four retrievers: [5]: (1) **BM25** (Robertson and Zaragoza, 2009): This serves as our baseline for the retrieval model performance. (2) **BGE-M3** (Chen et al., 2024): A retrieval model that shows a strong performance in many languages and domains. (3) **Human-Finetuned BGE-M3 (HF BGE-M3)**: A BGE-M3 model finetuned on NitiBench-CCL dataset. (4) **Auto-Finetuned BGE-M3 (AF BGE-M3)**: A finetuned BGE-M3 model on augmented NitiBench-CCL where we use `bge-reranker-v2-m3`[6] to rerank documents instead of legal experts.

The goal is to quantify the effectiveness between using a default BGE-M3, finetuned BGE-M3 on human-curated data, and finetuned BGE-M3 using an automatic reranking model. For all BGE-M3 variants, we use all three heads, and we weigh dense, multi-vector, and sparse scores at 0.4, 0.4, and 0.2, respectively.

4.2.2 LLM Choices

Once we identified the best retriever from the previous experiment, we fixed the retriever as HF BGE-M3 and evaluated the following LLMs: (1) GPT-4o[7] (Hurst et al., 2024), (2) Claude 3.5 Sonnet[8] (Anthropic, 2024b), (3) Gemini 1.5 Pro[9] (Reid et al., 2024), (4) Typhoon V2 70b (Pipatanakul et al., 2024) Our goal is to identify the performance of each LLM and select what LLM will be used for E2E evaluation (§ 4.2.3).

All LLMs use 3-shot examples randomly sampled from the training data, a temperature of 0.5, and a max output token limit of 2048.

4.2.3 E2E Evaluations

Building upon previous observations from §4.1 and §4.2, we defined our best setups for a RAG framework and compared each approach using NitiBench. Specifically, we compare four systems: (1) Parametric Knowledge: LLM-only baseline, (2) Naive RAG: Traditional RAG with naive chunking, (3) Proposed RAG: Enhanced with Hierarchy-aware Chunking and NitiLink, (4) RAG with Golden Context: Upper bound with ground truth context. For "Naive RAG," "Proposed RAG," and "Golden Context," we use Human-finetuned BGE-M3 as the retriever and Claude 3.5 Sonnet as the LLM. Unlike the Hierarchy-aware Chunking Experiment, the benchmark datasets for Naive RAG and Proposed RAG are not filtered to include only queries with relevant laws available in naive chunks. Additionally, in the Proposed RAG system, chunks are used as-is, without discarding those that contain sections absent from the naive chunks.

4.3 (RQ3) Long-Context LLMs

LCLMs like Gemini 1.5 Pro, which has a context window of over 2M tokens, can ingest all legislation in L into their prompt, potentially replacing the need for a retrieval model. We aim to explore Gemini's capabilities in Thai legal QA, where we use all legislation as a context. We evaluate LCLM in two settings: (1) LCLM as Generator: Gemini 1.5 Pro processes all laws as context, answering queries directly without any retrieval model. (2) LCLM as Retriever: Gemini 1.5 Pro retrieves top-k relevant documents, replacing traditional retrievers. We want to explore if Gemini 1.5 Pro can retrieve better documents under complex reasoning setups. Due to budget constraints, experiments are conducted on a 20% stratified subset of NitiBench-CCL and the full NitiBench-Tax dataset.

5 Results and Discussion

5.1 (RQ1) Impact of Tailored Components

Hierarchy-aware chunking achieves a slight but consistent advantage over the naive chunking strategy. From Table 1, the naive chunking strategy performs worse than hierarchy-aware chunking in terms of retrieval performance. This discrepancy likely arises because naive chunks often contain content from multiple sections, introducing "noise" that can negatively impact the retrieval model's ranking of relevant documents.

[5] We also conduct these experiments on more retrieval models. The results are outlined in Appendix I

[6] https://huggingface.co/BAAI/bge-reranker-v2-m3

[7] gpt-4o-2024-08-06

[8] claude-3-5-sonnet-20240620

[9] gemini-1.5-pro-002

However, in terms of end-to-end (E2E) performance, the system using Hierarchy-aware chunking only slightly outperforms the one using naive chunking. We suspect that this is because the LLM can effectively filter out the “noise” in the retrieved sections during answer generation. As a result, the coverage and contradiction scores are not significantly different between the two systems. Nevertheless, there remains a discrepancy in the E2E citation score.

Setting	Retriever Multi MRR (↑)	Retriever Recall (↑)	Coverage (↑)	Contradiction (↓)	E2E Recall (↑)	E2E Precision (↑)	E2E F1 (↑)
Naïve Chunking	0.786	0.935	86.6	**0.050**	0.882	0.613	0.722
Hierarchical-aware Chunking	**0.834**	**0.942**	**86.7**	0.054	**0.894**	**0.630**	**0.739**

Table 1: Effect of Chunking Configuration on E2E Performance on the NitiBench-CCL dataset.

NitiLink. The results from Table 2 show that there is no clear significant advantage when employing NitiLink in a RAG system.

Metric	NitiBench-CCL		NitiBench-Tax	
	Ref Depth 1	No Ref	Ref Depth 1	No Ref
Retriever Metrics				
Multi MRR (↑)	0.809	0.809	0.333	0.333
Recall (↑)	0.938	0.938	0.437	0.437
Referencer Metrics				
Multi MRR (↑)	0.800	**0.809**	**0.345**	0.333
Recall (↑)	**0.940**	0.938	**0.535**	0.437
Coverage (↑)	**86.3**	85.2	45.0	**50.0**
Contradiction (↓)	**0.051**	0.055	0.520	**0.460**
E2E Recall (↑)	**0.885**	0.880	**0.354**	0.333
E2E Precision (↑)	0.579	**0.601**	0.630	**0.64**
E2E F1 (↑)	0.700	**0.714**	**0.453**	0.438

Table 2: Effect of augmenter configuration on E2E performance, with separate grouping for Retriever and Referencer metrics.

In a complex legal query, NitiLink improves retriever recall, but the additional correct sections are usually ranked at the bottom. According to the result, we can clearly see that the recall was improved by 10%, yet MRR and MultiMRR were only marginally improved. This suggested that NitiLink does provide additional correct sections to the retrieved documents while the document that cited more positives by NitiLink is still ranked at the bottom of the retrieved documents.

Improvement in retriever recall from NitiLink doesn’t always translate to improvement in generation performance. In the NitiBench-Tax dataset, despite recall having a substantial improvement, E2E metrics declined. We hypothesized that the complexity of the NitiBench-Tax dataset demands advanced reasoning capabilities that the LLM, even with the correct documents, struggles to provide. Another potential reason that might affect the performance decline is the longer context that the LLM needs to process due to the higher amount of content added by NitiLink. We also further conduct more analysis on increasing reference depth in Appendix J.

5.2 (RQ2) Impact of Retriever and LLM

5.2.1 Retriever Models

Table 4 showed the performance of different retrieval models on both NitiBench-CCL and NitiBench-Tax . HF BGE-M3 achieved the best performance in NitiBench-CCL , as expected, since this is considered an “in-domain” data for the retriever. However, surprisingly, AF BGE-M3 achieves a very close performance compared to HF BGE-M3 (< 1%). This suggested that **for a simple legal query like NitiBench-CCL , `bge-reranker-v2-m3` is suitable to approximate the legal experts for annotating retrieval data.**

The NitiBench-Tax dataset, on the other hand, showed mixed results. HF BGE-M3 achieves the highest Hit rate, but only marginally compared to the base BGE-M3. Interestingly, the base BGE-M3 model achieves a higher Multi MRR compared to both HF and AF BGE-M3. We can interpret that **finetuning a retrieval model on a simple case, despite improved retrieval performance on generic legal QA, still can’t generalize towards a complex legal reasoning query.** Additionally, based on the following results, we opted to use **HF BGE-M3** as a retriever for E2E experiments due to their superior performance in both datasets.

We also conducted a detailed error analysis and identified error categories that highlight the current limitations of dense retrieval in Thai Legal QA. The results are summarized in Appendix L.

5.2.2 LLM Choices

The benchmark results of varying LLM are shown in Table 3. We also added the configuration of including and not including NitiLink in this experiment as well since the result in §5.1 showed no clear conclusion.

LLM	Referencer	Retriever Recall (↑)	E2E Recall (↑)	E2E Precision (↑)	E2E F1 (↑)	Coverage (↑)	Contradiction (↓)
NitiBench-CCL Dataset							
gpt-4o-2024-08-06	Ref Depth 1	0.938	0.885	0.579	0.700	86.3	0.051
	No Ref		0.880	**0.601**	**0.714**	85.2	0.055
gemini-1.5-pro-002	Ref Depth 1	0.938	0.895	0.491	0.634	87.3	0.042
	No Ref		0.892	0.512	0.651	86.5	0.048
claude-3-5-sonnet-20240620	Ref Depth 1	0.938	0.894	0.443	0.592	89.5	0.044
	No Ref		**0.901**	0.444	0.595	**89.7**	**0.040**
typhoon-v2-70b-instruct	Ref Depth 1	0.938	0.845	0.573	0.683	79.9	0.080
	No Ref		0.862	0.537	0.662	81.2	0.076
NitiBench-Tax Dataset							
gpt-4o-2024-08-06	Ref Depth 1	0.437	0.354	0.630	0.453	45.0	0.52
	No Ref		0.333	0.640	0.438	50.0	0.46
gemini-1.5-pro-002	Ref Depth 1	0.437	0.354	0.347	0.351	45.0	0.48
	No Ref		0.361	0.308	0.332	44.0	0.48
claude-3-5-sonnet-20240620	Ref Depth 1	0.437	**0.417**	0.577	**0.484**	49.0	0.56
	No Ref		0.389	0.554	0.457	51.0	**0.44**
typhoon-v2-70b-instruct	Ref Depth 1	0.437	0.333	0.453	0.384	**54.0**	0.46
	No Ref		0.326	**0.662**	0.437	42.0	0.58

Table 3: Effect of LLM configuration on end-to-end performance on NitiBench-CCL and NitiBench-Tax Datasets. For Retriver Recall, we show only the recall without taking into account of the referenced section for Ref Depth 1.

NitiBench-CCL

Model	HR/Recall	MRR
BM25	.658	.519
BGE-M3	.880	.824
HF BGE-M3	**.906**	**.850**
AF BGE-M3	.900	.840

NitiBench-Tax

Model	HR	Multi HR	Recall	MRR	Multi MRR
BM25	.480	.120	.211	.318	.171
BGE-M3	.720	**.294**	**.338**	.580	**.337**
HF BGE-M3	**.740**	.220	.331	.565	.320
AF BGE-M3	.700	.200	.310	**.587**	.329

Table 4: Retrieval Evaluation Results for BM25 and BGE-M3 Variants (Top-K = 5).

Recognizing the rapid pace of model development, we also include preliminary results of a newly released LLMs in Table 21. Due to computational constraints, these models were evaluated exclusively on the NitiBench-Tax with No Ref reference setting to provide a forward-looking perspective on performance.

Claude 3.5 Sonnet performs best generally for Thai Legal QA. Claude 3.5 Sonnet outperforms other proprietary LLMs for E2E recall and coverage on both NitiBench-CCL and NitiBench-Tax . One potential explanation for why Claude 3.5 Sonnet is good at Thai Legal QA is its competitive performance on the Thai Exam Benchmark[10], showcasing its nuanced understanding of the Thai language. Nevertheless, `gpt-4o-2024-08-06`, despite having a lower coverage score, yields a surprisingly high E2E F1 score in NitiBench-CCL , highlighting a dominant performance in selecting the relevant section to be cited in the generated answer. However, it's performance on NitiBench-CCL is still subpar to Claude 3.5 Sonnet.

Effective of incorporating NitiLink is still inconclusive. On the NitiBench-Tax dataset, most models struggle to reason over the relevant documents based on the performance difference compared to the NitiBench-CCL dataset. Claude 3.5 Sonnet clearly outperforms `gpt-4o-2024-08-06` and `gemini-1.5-pro-002` in most E2E metrics. However, `typhoon-v2-70b-instruct`, an open-sourced model, unexpectedly became the only model that incorporated NitiLink and obtained an improved Coverage and Contradiction score.

Additionally, we analyzed discrepancies between LLM citation recall and retrieval recall, including instances of hallucinated citations. Details are provided in Appendix M.

5.2.3 E2E Evaluations

Given the previous experiments, we have verified the effectiveness of using HF BGE-M3 as a retriever and Claude 3.5 Sonnet as an LLM for RAG. Since the results for incorporating NitiLink were inconclusive, we removed the use of NitiLink for this experiment since it significantly reduced prompt length. We presented the results of a full RAG pipeline in Table 5.

From the results, we use Claude 3.5 Sonnet as the main LLM for the E2E experiment since it

[10] https://huggingface.co/spaces/ThaiLLM-Leaderboard/leaderboard

Setting	Coverage (↑)	Contradiction (↓)	E2E Recall (↑)	E2E Precision (↑)	E2E F1 (↑)
NitiBench-CCL Dataset					
Parametric	60.3	0.199	0.188	0.141	0.161
Naïve RAG	77.3	0.097	0.745	0.370	0.495
Proposed RAG	**89.7**	**0.040**	**0.901**	**0.444**	**0.595**
Golden Context	93.4	0.034	0.999	1.000	1.000
NitiBench-Tax Dataset					
Parametric	46.0	0.480	**0.458**	**0.629**	**0.530**
Naïve RAG	50.0	0.460	0.306	0.463	0.368
Proposed RAG	**51.0**	**0.440**	0.389	0.554	0.457
Golden Context	52.0	0.460	0.694	1.000	0.820

Table 5: E2E evaluation results on NitiBench-CCL and NitiBench-Tax. **Parametric** represents naive few-shot prompts without additional context. **Naive RAG** is a conventional RAG with naive chunking. **Proposed RAG** utilized hierarchy-aware chunking. **Golden Context** remove retrieval component in RAG, augmented the prompt with ground-truth positives.

yields the most consistent performance across all metrics. Additionally, the proposed RAG with Hierarchy-aware chunking provides the best coverage and contradiction score for both NitiBench-CCL and NitiBench-Tax . On the other hand, all setups, including golden context, which is the upper bound, still struggle on NitiBench-Tax . This indicates that *utilizing RAG alone is insufficient to solve sophisticated legal QA queries, especially when legal reasoning is required.*

We also see a surprising pattern in the parametric knowledge setup where Claude 3.5 Sonnet yields an astonishingly high E2E F1 score. To further investigate this, we inspect the cited section that was generated by LLM. Surprisingly, out of 105 sections cited from LLM parametric knowledge, 58 of them *were not* even retrieved by the best retriever. Among those 58 cited documents, 26 of those were correct. In contrast, only 5 of 101 sections cited by the proposed RAG system are *not* retrieved. This indicates that retriever performance significantly constrains RAG systems, especially with complex queries like those in NitiBench-Tax . We also further hypothesize that the gains in performance might come from the fact that Tax cases data are more readily available on the web, increasing the chance of overlap in pre-training. However, we emphasize that we have no direct supporting evidence for this hypothesis.

5.3 (RQ3) LCLM Performance

LCLM still underperforms RAG on Thai Legal QA both in simple and complex datasets. In Table 6, we can see that LCLM performance for both coverage and contradiction is still below our proposed RAG. This performance gap may stem from degradation when processing extremely long contexts (1.2 million tokens). The results suggest that while an LCLM-based Thai legal QA system is feasible, its performance remains significantly behind RAG-based counterparts, highlighting areas for further improvement.

Setting	Coverage (↑)	Contradiction (↓)	E2E Recall (↑)	E2E Precision (↑)	E2E F1 (↑)
NitiBench-CCL Dataset					
Parametric	60.6	0.198	0.197	0.147	0.169
Naïve RAG	77.7	0.092	0.740	0.379	0.501
Proposed RAG	**90.1**	**0.028**	**0.920**	0.453	0.607
LCLM	83.2	0.063	0.765	**0.514**	**0.615**
Golden Context	94.2	0.025	0.999	1.0	0.999
NitiBench-Tax Dataset					
Parametric	46.0	0.480	**0.458**	**0.629**	**0.530**
Naïve RAG	50.0	0.460	0.306	0.463	0.368
Proposed RAG	**51.0**	**0.440**	0.389	0.554	0.457
LCLM	36.0	0.620	0.410	0.484	0.444
Golden Context	52.0	0.460	0.694	1.000	0.820

Table 6: E2E results including LCLM on a 20% stratified subset of the test data on NitiBench-CCL dataset and full NitiBench-Tax dataset. We use `gemini-1.5-pro-002` for LCLM.

LCLM-as-a-retriever was feasible technically but still unfeasible economically. Table 7 showed the performance of LCLM-as-a-retriever. On a simple query dataset, NitiBench-CCL , the performance is still subpar to that of BGE-M3 and its variants. We suspect this might be due to too much distractor in a longer context document, resulting in a lower performance. However, on a complex retrieval dataset, NitiBench-Tax , LCLM-as-a-retriever outperforms all retrieval models in all metrics. This indicates the feasibility of using LCLM as a retriever. Nevertheless, performance compared to the cost and latency introduced makes this approach worse trade-offs than using a conventional embedding model. We further discuss the effect of the relevant section position in the context of the E2E performance in Appendix K.

5.4 Effectiveness of Multi-label Metrics

To further validate the effectiveness of our proposed multi-label metrics, we compute the correlation between conventional retrieval metrics (Hit

NitiBench-CCL Dataset

Model	HR/Recall	MRR
BM25	.663	.549
BGE-M3	.888	.779
HF BGE-M3	**.909**	**.819**
AF BGE-M3	.909	.807
LCLM	.776	.667

NitiBench-Tax Dataset

Model	HR	Multi HR	Recall	MRR	Multi MRR
BM25	.480	.120	.211	.318	.171
BGE-M3	.720	.240	.338	.580	.337
HF BGE-M3	.740	.220	.331	.565	.320
AF BGE-M3	.700	.200	.310	**.587**	.329
LCLM	**.760**	**.320**	**.418**	**.587**	**.370**

Table 7: Retrieval Evaluation Results (Top-K = 5) for BM25, BGE-M3 variants, and LCLM-as-a-retriever on the NitiBench-CCL and NitiBench-Tax datasets. We conducted this experiment on a 20% stratified subset of the test set due to budget constraints.

Rate and MRR) compared to its multi-label variant. We use eight retriever model performances (see Appendix I) to measure the correlation between retrieval and the E2E metric. The result was presented in Table 8.

According to the result, we can see that our Multi-MRR and Multi-Hit Rate have a higher correlation compared to conventional MRR and hit rate. These results emphasize the importance of using multi-label metrics in legal QA setups.

	Coverage (↑)	Contradiction (↓)	E2E F1 (↑)
Hit Rate	0.741	-0.672	0.780
Multi Hit Rate	**0.989**	**-0.986**	0.984
MRR	0.906	-0.859	0.933
Multi MRR	**0.989**	-0.973	**0.991**

Table 8: Correlation between conventional and multi-retrieval metrics with evaluation measures using data from 8 retrievers (Appendix I)

6 Conclusion

This work introduces ThaiLegal, a benchmark for Thai legal QA built on two domains, CCL and Tax Law, which are both technically demanding and practically relevant. We propose tailored datasets, retrieval, and end-to-end metrics, and evaluate RAG and long-context LLM approaches. Our findings highlight the limitations of current systems in legal reasoning, especially under reference-heavy conditions, and demonstrate the value of domain-specific techniques like hierarchy-aware chunking. ThaiLegal provides a foundation for advancing legal NLP in underrepresented languages and for developing more grounded, reliable QA systems.

Limitations

Despite being the first E2E benchmark for Thai legal QA, both of our datasets still have several limitations.

WangchanX-Legal-ThaiCCL-RAG and NitiBench-CCL Limitations. The WangchanX-Legal-ThaiCCL-RAG training split was constructed in a semi-synthetic approach with human quality control for the training set and a fully human-annotated process for the test set (NitiBench-CCL). While this design effectively manages costs, it presents several issues.

First, let us discuss the ambiguity of queries in the test set caused by single-section sampling. Annotators create questions based solely on a single sampled section from one of the 21 available laws, often leading to queries that are too general and overlap with multiple related sections. This lack of specificity can confuse language models, which incorporate multiple sections even when the query targets just one. This also applies to training data where the answer was first generated by LLM, given only one law section to the prompt.

Second, the absence of truly multi-label queries in both the training and test sets. While annotators in the training set select multiple relevant sections from retrieved documents, the questions themselves originate from single sections, restricting their multi-label nature. This limits the dataset's ability to evaluate reasoning across multiple legal provisions. Although NitiBench-Tax partially addresses this gap by including queries requiring multi-label reasoning, this issue persists across the broader dataset.

Finally, the dataset's queries lack natural phrasing and fail to reflect how real users would pose questions in a Thai legal QA system. Current queries are often overly formal or influenced by the dataset construction process, making them less representative of typical user input.

These challenges, ambiguity in queries, the absence of multi-label scenarios, and unnatural phrasing, highlight areas for improvement to enhance both WangchanX-Legal-ThaiCCL-RAG and NitiBench-CCL dataset's relevance and effectiveness for Thai legal QA systems.

Reliability of Multi-label Metrics. Our proposed Multi-HitRate and Multi-MRR, although shown in §5.4 to correlate more strongly with the E2E metrics, were calculated using only eight retrievers. This limited data point is primarily due to the substantial cost associated with inferencing a larger pool of retrievers, coupled with the scarcity of available retriever models specifically tailored for the Thai legal domain. Consequently, while our initial findings are promising, the restricted number of retrievers may impact the generalizability of these metrics. Future work should explore expanding the set of retrievers and consider additional domain-specific datasets to further validate and potentially refine the robustness of our multi-label evaluation framework.

Legal Reasoning Evaluation. Beyond Coverage, Contradiction, and Citation scores, legal reasoning is crucial for Legal QA. It differs from general reasoning by operating within a structured legal framework, demanding strict adherence to legal principles and precise interpretation of authoritative sources. Evaluating legal reasoning, where the process matters as much as the answer, enhances the performance assessment. This work, although highlighting how to evaluate the final answer, still lacks the measurement of LLM legal reasoning and focuses specifically on the final generated response. Existing studies explore reasoning evaluation in LLMs using metrics for semantic alignment, logical inference, and language coherence (Golovneva et al., 2023) and qualities like correctness and informativeness (Prasad et al., 2023). LLM Reasoner (Hao et al., 2024) automate error categorization using LLMs. However, reasoning evaluation for LLMs, especially in the Thai legal domain, remains challenging. Obstacles include defining "good" legal reasoning and acquiring datasets that require complex legal reasoning beyond simple lookups.

Acknowledgement

This work would not have been possible without the significant contributions of several individuals and teams. We sincerely thank Supavich Punchun for facilitating NitiBench-CCL data preparation and Apiwat Sukthawornpradit, Watcharit Boonying, and Tawan Tantakull for preparing the NitiBench-Tax Dataset. We are also grateful to the VISAI team for their vital quality control on the LLM-as-a-judge validation and to our legal expert annotators for their meticulous annotations.

We gratefully acknowledge the Vidyasirimedhi Institute of Science and Technology (VISTEC) for providing the computing resources and infrastructure that supported this project.

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A WangchanX-Legal-ThaiCCL-RAG Dataset Curation

A.1 Curating Training Data

This section outline the data collection process of WangchanX-Legal-ThaiCCL-RAGdataset. Consider dataset notations from §3.1. Questions q_i are generated using Gemini 1.5 Pro (Reid et al., 2024) based on the given section sampled from L. Then, we retrieve relevant candidate sections p_k for each question using BGE-M3 (Chen et al., 2024) resulting in positive documents T_i. The label y was generated using Llama-3-70B (Dubey et al., 2024) (or Claude 3 Sonnet (Anthropic, 2024a) if Llama-3-70B reject the answer). Finally, the generated answer y and positive sections T are further validated by legal experts for assuring data quality. The legal experts either remove irrelevant section, add more relevant sections, or rerank sections in T and adjust y to ensure phrases are all correct. Thus, for our training data, queries q correspond to T_i where $|T_i| \geq 1$ and are considered multi-label. The legislation list for WangchanX-Legal-ThaiCCL-RAGdataset curation is in Table 9. Figure 1 shows the data collection process for WangchanX-Legal-ThaiCCL-RAG's training split.

A.2 Curating Test Data

For the test dataset, all queries q_i and generated answer y_i were manually crafted by legal experts given a single section sampled from L. Each manually crafted question was carefully quality-assured by a second legal expert. As a result, the test data are single-labeled ($|T_i| = 1$), whereas the training data are multi-labeled.

A.3 Annotator Profile and Cost

Since we are curating a dataset specifically in the Thai legal domain, it is important to ensure that our annotators have a strong background in Thai legal knowledge. To achieve this, we recruited legal experts through law school professors via their available channels, such as their social networks [11]. We received a total of 97 applications and selected 34 annotators. Their occupations include law students, recent law school graduates, and employees at law firms. Furthermore, all annotators were informed that the data would be used for an open-source research project, and their participation implied consent to this usage.

We compensate annotators per completed task, which includes curating the training set, conducting quality checks, and curating the test set. Tasks are randomly assigned, and we adjust the distribution based on each annotator's speed of completion. Payment is determined per task[12], with each task compensated differently based on its difficulty. The tasks are as follows:

1. Rerank retrieved documents for the fine-tuning dataset: 5 THB (approximately \$0.15) per task.

2. Validate, correct, and reject the generated answers for both training and test data: 10 THB (approximately \$0.30) per task.

3. Create a question and answer based on a given law section (for the test set): 30 THB (approximately \$0.89) per task.

The total cost spent solely on annotators is approximately 274,240 THB (roughly \$8076).

[11] The call for annotation post can be accessed on Facebook: Facebook Post

[12] To simplify the calculations, we use a fixed conversion rate of 34 Thai baht per \$1.

Legislation	Legal Terminology	Training	Test
Organic Act on Counter Corruption, B.E. 2561	organic law	✓	
Civil and Commercial Code	code	✓	✓
Revenue Code	code	✓	✓
Accounting Act, B.E. 2543	act	✓	✓
Accounting Profession Act, B.E. 2547	act	✓	✓
Act on Disciplinary Offenses of Government Officials Performing Duties in Agencies Other than Government Agencies, B.E. 2534	act	✓	
Act on Offences of Officials Working in State Agencies or Organizations, B.E. 2502	act	✓	
Act on Offenses Relating to Registered Partnerships, Limited Partnerships, Companies Limited, Associations and Foundations, B.E. 2499	act	✓	✓
Act on the Establishment of Government Organizations, B.E. 2496	act	✓	
Act on the Management of Shares and Stocks of Ministers, B.E. 2543	act	✓	
Act Repealing the Agricultural Futures Trading Act, B.E. 2542 B.E. 2558	act	✓	
Budget Procedure Act, B.E. 2561	act	✓	
Business Registration Act, B.E. 2499	act	✓	✓
Chamber of Commerce Act, B.E. 2509	act	✓	✓
Derivatives Act, B.E. 2546	act	✓	✓
Energy Conservation Promotion Act, B.E. 2535	act	✓	✓
Energy Industry Act, B.E. 2550	act	✓	✓
Financial Institutions Business Act, B.E. 2551	act	✓	✓
Fiscal Discipline Act, B.E. 2561	act	✓	
Foreign Business Act, B.E. 2542	act	✓	✓
Government Procurement and Supplies Management Act, B.E. 2560	act	✓	
National Economic and Social Development Act, B.E. 2561	act	✓	
Petroleum Income Tax Act, B.E. 2514	act	✓	✓
Provident Fund Act, B.E. 2530	act	✓	✓
Public Limited Companies Act, B.E. 2535	act	✓	✓
Secured Transactions Act, B.E. 2558	act	✓	✓
Securities and Exchange Act, B.E. 2535	act	✓	✓
State Enterprise Capital Act, B.E. 2542	act	✓	
State Enterprise Committee and Personnel Qualifications Standards Act, B.E. 2518	act	✓	
State Enterprise Development and Governance Act, B.E. 2562	act	✓	
State Enterprise Labor Relations Act, B.E. 2543	act	✓	
Trade Association Act, B.E. 2509	act	✓	✓
Trust for Transactions in Capital Market Act, B.E. 2550	act	✓	✓
Emergency Decree on Digital Asset Businesses, B.E. 2561	emergency decree	✓	
Emergency Decree on Special Purpose Juristic Person for Securitization, B.E. 2540	emergency decree	✓	✓

Table 9: NitiBench-CCL Legislation (High to Low Legislative Rank, Alphabetical): Training and Test Set Distribution

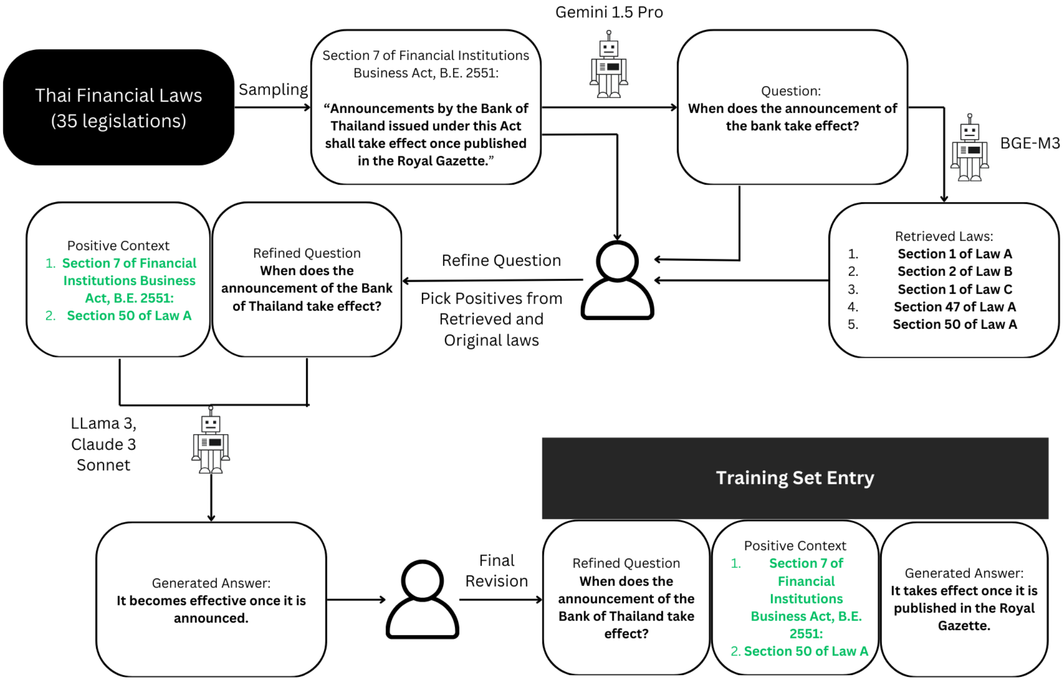

Thai Financial Laws (35 legislations)
Sampling
Section 7 of Financial Institutions Business Act, B.E. 2551:
"Announcements by the Bank of Thailand issued under this Act shall take effect once published in the Royal Gazette."
Gemini 1.5 Pro
Question:
When does the announcement of the bank take effect?
BGE-M3
Retrieved Laws:
1. Section 1 of Law A
2. Section 2 of Law B
3. Section 1 of Law C
4. Section 47 of Law A
5. Section 50 of Law A
Refine Question
Pick Positives from Retrieved and Original laws
Positive Context
1. Section 7 of Financial Institutions Business Act, B.E. 2551:
2. Section 50 of Law A
Refined Question
When does the announcement of the Bank of Thailand take effect?
LLama 3, Claude 3 Sonnet
Generated Answer:
It becomes effective once it is announced.
Final Revision
Training Set Entry
Refined Question
When does the announcement of the Bank of Thailand take effect?
Positive Context
1. Section 7 of Financial Institutions Business Act, B.E. 2551:
2. Section 50 of Law A
Generated Answer:
It takes effect once it is published in the Royal Gazette.

Figure 1: Overall dataset construction pipeline for training set of NitiBench-CCL

B Nitibench-CCL Dataset Curation

NitiBench-CCL extends the original WangchanX-Legal-ThaiCCL-RAG's test set by applying additioanl postprocessing step. Since the annotated contextual information includes the full content of relevant legal sections, we further preprocess the test set by extracting only the names of the referenced legal sections from the annotations and deduplicate

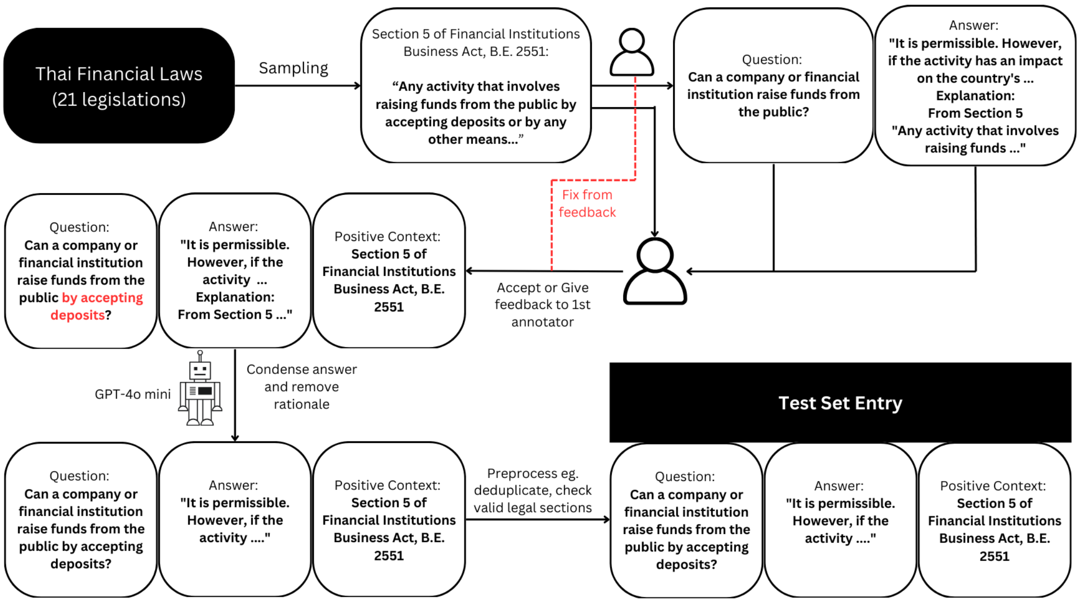

Thai Financial Laws (21 legislations)
Sampling
Section 5 of Financial Institutions Business Act, B.E. 2551:
"Any activity that involves raising funds from the public by accepting deposits or by any other means..."
Question: Can a company or financial institution raise funds from the public?
Answer: "It is permissible. However, if the activity has an impact on the country's ... Explanation: From Section 5 "Any activity that involves raising funds ..."
Fix from feedback
Accept or Give feedback to 1st annotator
Question: Can a company or financial institution raise funds from the public by accepting deposits?
Answer: "It is permissible. However, if the activity ... Explanation: From Section 5 ..."
Positive Context: Section 5 of Financial Institutions Business Act, B.E. 2551
GPT-4o mini
Condense answer and remove rationale
Test Set Entry
Question: Can a company or financial institution raise funds from the public by accepting deposits?
Answer: "It is permissible. However, if the activity ...."
Positive Context: Section 5 of Financial Institutions Business Act, B.E. 2551
Preprocess eg. deduplicate, check valid legal sections
Question: Can a company or financial institution raise funds from the public by accepting deposits?
Answer: "It is permissible. However, if the activity ...."
Positive Context: Section 5 of Financial Institutions Business Act, B.E. 2551

Figure 2: Overall dataset construction pipeline for test set of NitiBench-CCL

entries with the same questions. Figure 2 illustrates the data collection process for NitiBench-CCL .

C Nitibench-Tax Dataset Curation

To evaluate the generalization capability of the system, we curated an additional dataset derived from publicly available resources in the Thai financial legal domain. Specifically, this dataset was created by scraping tax-related cases from the Revenue Department's official website[13]. These cases represent authentic inquiries or requests (with personally identifiable information removed) submitted to the department. Each case includes the original inquiry or request, the official response, and metadata such as the case ID and submission date. We extracted references to legislative sections mentioned in both the inquiry and the response as case attributes using `gpt-4o-mini-2024-07-18` for any preprocessing steps involving the use of LLM used during constructing NitiBench-Tax . The dataset was filtered to retain only cases referencing laws within the 35 Thai financial law codes and to eliminate duplicate references within individual entries. Some cases, however, involve inquiries requesting discretionary decisions from the department-such as extensions for tax deadlines or tax exemptions-rather than informational responses based on statutory interpretation. Since these cases are outside the scope of our work, which focuses on law-based reasoning, they were identified using an LLM and subsequently removed.

Additionally, to align with our evaluation objectives, the department's responses were condensed to essential answers, excluding detailed explanations and rationales. Finally, we restricted the dataset to cases from 2021 onward, reflecting the most recent legislative updates. The resulting NitiBench-Tax consists of 50 cases, predominantly related to the Revenue Code, with an average of three referenced legal sections per case. This dataset provides a challenging testbed for evaluating system performance in a specialized domain requiring nuanced legal reasoning and multi-label retrieval.

The complete dataset construction pipeline of NitiBench-Tax is outlined in Figure 3.

D Dataset Statistics

The extensive dataset statistics of the constructed NitiBench-CCL and NitiBench-Tax is displayed in Table 10, 11 and 12

The majority of the law sections covered in this

[13] https://www.rd.go.th

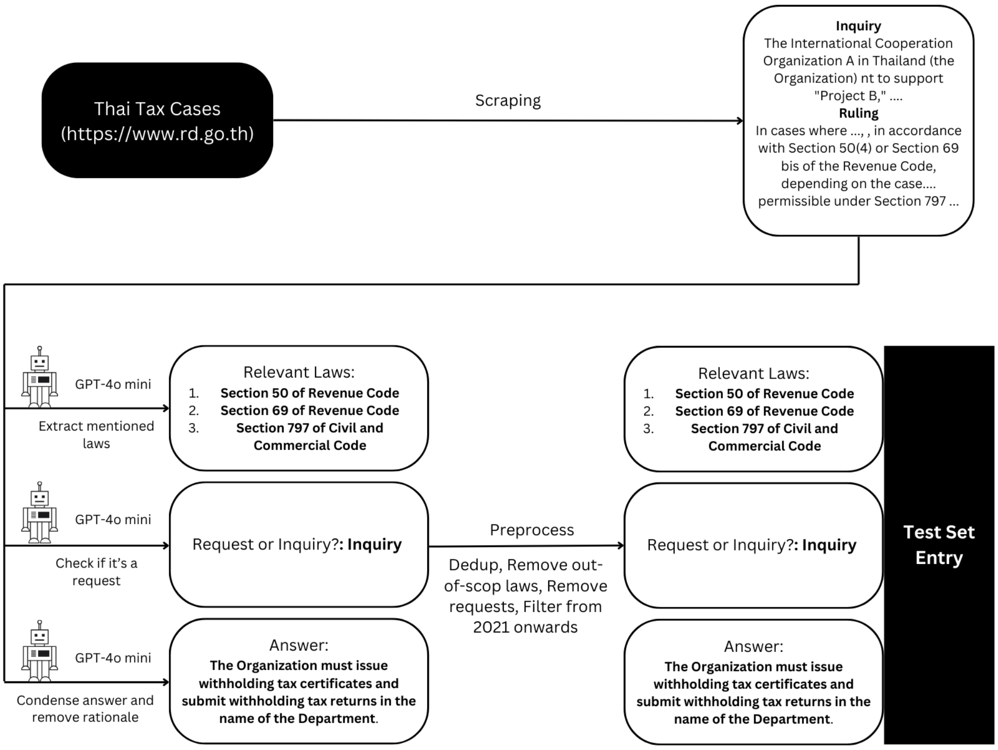

Thai Tax Cases (https://www.rd.go.th)
Scraping
Inquiry
The International Cooperation Organization A in Thailand (the Organization) nt to support "Project B," ....
Ruling
In cases where ..., , in accordance with Section 50(4) or Section 69 bis of the Revenue Code, depending on the case.... permissible under Section 797 ...
GPT-4o mini
Extract mentioned laws
Relevant Laws:
1. Section 50 of Revenue Code
2. Section 69 of Revenue Code
3. Section 797 of Civil and Commercial Code
GPT-4o mini
Check if it's a request
Request or Inquiry?: Inquiry
GPT-4o mini
Condense answer and remove rationale
Answer:
The Organization must issue withholding tax certificates and submit withholding tax returns in the name of the Department.
Preprocess
Dedup, Remove out-of-scop laws, Remove requests, Filter from 2021 onwards
Relevant Laws:
1. Section 50 of Revenue Code
2. Section 69 of Revenue Code
3. Section 797 of Civil and Commercial Code
Request or Inquiry?: Inquiry
Answer:
The Organization must issue withholding tax certificates and submit withholding tax returns in the name of the Department.
Test Set Entry

Figure 3: Overall dataset construction pipeline for NitiBench-Tax

Metric	CCL	Tax
Number of entries	3729	50
Number of unique sections as positive contexts	3582	59
Minimum number of positive contexts	1	1
Mean ± SD number of positive contexts	1 ± 0	2.62 ± 1.96
Maximum number of positive contexts	1	9
Minimum length of query (characters)	10	163
Mean ± SD length of query (characters)	86.5 ± 54.4	941.8 ± 708.6
Maximum length of query (characters)	751	3818
Minimum length of answer (characters)	2	28
Mean ± SD length of answer (characters)	134.2 ± 142.1	140.2 ± 82.7
Maximum length of answer (characters)	1904	405

Table 10: Summary statistics for NitiBench-CCL and NitiBench-Tax datasets

Legislation	Positive Counts
Civil and Commercial Code	1617
Revenue Code	484
Securities and Exchange Act, B.E. 2535	294
Public Limited Companies Act, B.E. 2535	186
Financial Institutions Business Act, B.E. 2551	165

Table 11: Distribution of positive context legislation in NitiBench-CCL

Legislation	Positive Counts
Revenue Code	116
Civil and Commercial Code	10
Securities and Exchange Act, B.E. 2535	3
Accounting Act B.E. 2543	2

Table 12: Distribution of positive context legislation in NitiBench-Tax

split were from the Thai Civil and Commercial Code, with over 1600 instances, followed by the Revenue Code. This predominance is due to the extensive number of sections within these legislations, making them more commonly cited in the dataset. The average number of relevant laws is one, owing to the fact that the test set for NitiBench-CCL was manually curated, as explained in Appendix B. The query length distribution averaged 86.5 characters, with a maximum of 751 characters.

The NitiBench-Tax dataset shows a clear dominance of the Revenue Code, which aligns with its basis in tax rulings issued by the Revenue Department. Unlike conventional legal cases, which are generally governed solely by the Civil and Commercial Code, tax rulings often address complex scenarios requiring interpretation across multiple legislations. As a result, queries tend to be more complex, with the number of relevant sections per query ranging from one to ten (mean $\approx$ 2.62). Furthermore, the intricate nature of tax-related inquiries is reflected in the longer query lengths compared to the NitiBench-CCL dataset.

E Dataset Samples

E.1 NitiBench-CCL Example #1

Question: Can the Bank of Thailand propose the enactment of a Royal Decree for regulating business operations? If so, how?

Relevant Laws:

- **Financial Institutions Business Act B.E. 2551 (2008), Section 5:** For any business operation involving mobilizing funds from the public through deposits or other means, providing credit...

Answer: Yes, it can be proposed if the operation affects the overall economy of the country and there is no specific law regulating it.

E.2 NitiBench-CCL Example #2

Question: Regarding instruments that require a government official's signature, what are these officials prohibited from doing?

Relevant Laws:

- **Revenue Code Section 119:** For instruments which a government or municipal official must sign or acknowledge, instruments which must be executed before a government or municipal official, or instruments which must be recorded by a government or municipal official, the official is prohibited from signing in acknowledgement, permitting execution, or recording them until the duty has been paid by affixing stamps for the full amount according to the rates in the schedule annexed to this Chapter and cancelling them. However, this shall not prejudice the right to collect the surcharge under Section 113 and Section 114.

Answer: Officials are prohibited from signing in acknowledgement, permitting execution, or recording the instrument until the duty has been paid by affixing stamps for the full amount according to the rates in the schedule annexed to this Chapter and cancelling them.

E.3 NitiBench-Tax Example

Question: The Regional Revenue Office consults on a case regarding a VAT refund claim involving the deduction of input tax related to income generated abroad in the calculation of VAT. The summarized facts are:

- The Company exports printed and dyed fabric to foreign countries and is entitled to VAT at the zero rate (0%).
- Two export methods:
  1. Direct sale to customers abroad (reported as zero-rate VAT).
  2. Exported fabric to China for tailoring into finished garments, then reshipped to customers in Panama, with the Company named as exporter.
- The Company reported these exports as zero-rate VAT in the P.P.30 form and recognized them as income for corporate income tax under Section 65.

Relevant Laws:

- **Revenue Code Section 77/1:** In this Chapter, unless...
- **Revenue Code Section 80/1:** The zero percent (0%)...
- **Revenue Code Section 82/3:** (not explicitly shown but referenced)
- **Revenue Code Section 82/4:** (not explicitly shown but referenced)
- **Revenue Code Section 82/5:** Input tax in the following...
- **Revenue Code Section 65:** Income subject to tax...

Answer: Based on the facts, the Company hired a company in China to produce or tailor finished garments. The Company undertook customs procedures to export fabric to the company in China for use as raw material in the production or tailoring of finished garments, wherein the Company's name appeared as the exporter on the Bill of Lading and the Export Declaration Form. This qualifies as an export according to Section 77/1 (14) of the Revenue Code. Therefore, the Company is an exporter of raw materials entitled to VAT at the zero rate (0%) according to Section 80/1 (1) of the Revenue Code.

The VAT paid on purchasing the fabric and on export-related expenses is input tax related to a zero-rated business activity. It may be deducted from the Company's output tax under Sections 82/3 and 82/4. However, such input tax must not fall under the types listed as non-creditable in Section 82/5.

F Judge LLM Performance

Table 13 showed the final agreement score between human-annotated coverage and contradiction score compared to judge LLM-generated ones. LLM-as-a-judge is used for automatic evaluation, with prompts refined to achieve high agreement with human annotations (F1 > 0.8). The LLM-as-a-judge score is generated by `gpt-4o-2024-08-06` (Hurst et al., 2024) model with temperature of 0.3.

Metric	Dataset	Precision	Recall	F1-score	Support
Coverage	NitiBench-CCL	.88	.88	.88	200
	NitiBench-Tax	.83	.83	.83	150
Contradiction	NitiBench-CCL	.98	.97	.98	200
	NitiBench-Tax	.92	.91	.91	150

Table 13: Table displaying the weighted average precision, recall, and F1-score between metrics computed by LLM and annotated by human experts

To further analyze this agreement, we present confusion matrices for NitiBench-CCL and NitiBench-Tax in Tables 14 and 15, respectively. As observed in the confusion matrices, it is rare for the LLM-as-a-judge to misclassify a ground truth score of 0 as 100 or vice versa. Most errors occur in the confusion between 50 and 100, as well as between 0 and 50. We consider this acceptable since the boundaries between these scores can sometimes be subjective. Although the agreement scores did not reach our initial expectations after multiple iterations, we conclude that it remains reliable, achieving at least 80% accuracy for the coverage score and at least 90% accuracy for the contradiction score.

	Predicted 0	Predicted 50	Predicted 100
Ground Truth 0	8	2	3
Ground Truth 50	2	29	7
Ground Truth 100	1	9	139

Table 14: Confusion matrix for coverage agreement score on 200 NitiBench-CCL samples

	Predicted 0	Predicted 50	Predicted 100
Ground Truth 0	43	5	1
Ground Truth 50	6	35	6
Ground Truth 100	2	5	47

Table 15: Confusion matrix for coverage agreement score on 150 NitiBench-Tax samples

G Thai Legal System

Thailand's legal system operates within a hierarchical structure, where lower-level laws must not contradict higher ones. The hierarchy includes the Constitution, Organic Laws, Acts/Codes, Emergency Decrees, Royal Decrees, Ministerial Regulations, and Local Ordinances (Chuathai, 2023). The Constitution is the highest law of Thailand, providing foundational governance and protection of people's rights. Acts and Codes are primary legislation enacted by the legislative branch, with Acts encompassing individual laws and Codes structuring provisions in related subject matters, such as the Criminal Code.

Acts and Codes are structured hierarchically. The structure proceeds from broad categories to increasingly specific details (Book, Title, Chapter, Division, Section, Subsection, Clause), with **Sections** being the fundamental legal units. This structure is designed for efficient navigation but creates challenges for RAG systems, specifically regarding how to chunk legislative documents while preserving the meaning. Furthermore, Thai legal text often utilizes inter-section references. For instance, understanding Section 260 of the Criminal Code

> "Whoever uses, sells, offers for sale, exchanges, or offers to exchange a ticket arising from the acts described in *section 258* or *section 259* shall be liable to imprisonment not exceeding one year or a fine not exceeding twenty thousand baht, or both." (The Kingdom of Thailand, 2022)

requires the context from section 258 and 259, which are not included in the same text segment. This raises questions about automatic retrieval and augmentation of referenced sections.

H Naive Chunking

We define naive chunking strategy as the best traditional chunking method that minimized "information loss" compared to our proposed hierarchical-aware chunking. Traditional chunking methods such as

- **Character Chunking:** Chunking is based purely on a fixed number of characters.
- **Recursive Chunking:** Chunking using various document structure-related separators.
- **Line Chunking:** Chunking based solely on newline characters.

often split sections naively via naive heuristic, leading to contextual "information loss" in section information. We quantify "information loss" via following metrics:

1. **Sections/Chunk**: Average sections per chunk.
2. **Chunks/Section**: Average chunks covering a section.
3. **Fail Chunk/Section Ratio**: Chunks/sections which are not fully covered.
4. **Uncovered Section Ratio**: Sections which are not covered at all.

Table 16 showed the information loss of different traditional chunking strategy. Notably, we decompose the problem of finding the best naive chunking strategy into two steps. First, we seek to find the best traditional chunking algorithm with the default parameter settings. After that, we further tune the chunking parameters-chunk size and overlap size-that further minimized the information loss. The best setups that will be referred as "naive chunking strategy" is line chunking using chunk size of 553 and overlap size of 50.

I Full Retrieval Model Performance

In addition to BM25 and BGE-M3 variants showed in the main experiment, we also conduct this experiments on various embeddings as well. The results is showed in Table 20. We choose 8 embeddings models for this experiment as follows:

1. BM25 (Robertson and Zaragoza, 2009)
2. JinaAI Colbert V2 (Jha et al., 2024)
3. JinaAI Embeddings V3 (Sturua et al., 2024)
4. NV-Embed V1 (Lee et al., 2024a)
5. BGE-M3 (Chen et al., 2024)
6. Human-Finetuned BGE-M3
7. Auto-Finetuned BGE-M3
8. Cohere Embeddings [14]

J Adding More Reference Depth

Adding more reference depth improves retrieval performance when the question requires extensive legal reasoning. To further investigate the effect of increasing NitiLink depth towards performance, we examined the relationship between *NitiLink's maximum depth*, *retrieval performance gains* (`Mean Diff` on the y-axis), and *the total number of sections NitiLink resolves* (see Figures 4). For the Tax dataset, retrieval performance improves as reference depth increases, peaking at a depth of 6. However, this comes at the cost of increased context length, reaching approximately 60 sections per query. While the improvement in retrieval performance could be attributed to retrieving more sections, thereby increasing the hit rate, after extensive recursive reference resolution in NitiBench-Tax dataset, the results for the NitiBench-CCL dataset indicate that this is not always the case. For the NitiBench-CCL dataset, retrieval gains remain minimal and plateau after a depth of 2, despite resolving up to 30 sections at a depth of 9. We suspect this is due to the NitiBench-CCL dataset requiring only one relevant law per entry, eliminating the need for complex legal reasoning during retrieval.

K LCLM Performance Analysis

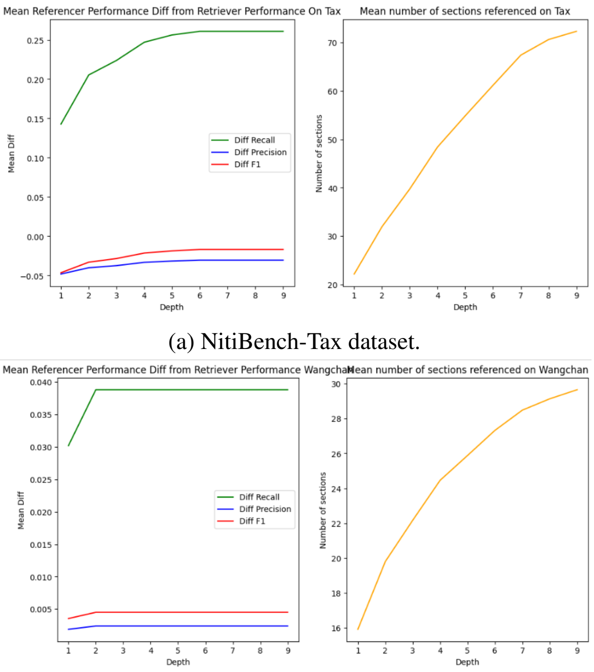
The effect of the relevant context position in the overall documents on the performance of the system is analyzed on the sampled WCX dataset under the LCLM setting. The resulting performance is binned every 100,000 characters by the maximum depth of the relevant laws that need to be retrieved, and the coverage, contradiction, and E2E F1 of each bin are averaged and plotted in figure 5.

From the resulting plot, there is only a slight decrease in the coverage score and a slightly greater increase in the contradiction score as the depth increases. However, there is a significant drop in the E2E F1 score as the depth increases. Therefore, it can be concluded that **the depth of the relevant laws only mildly affects the coverage and contradiction score while its ability to cite applicable laws clearly has a negative impact.** Furthermore, the gains in performance in LCLM-as-a-retriever when increasing the number of retrieved documents are lower as compared to the gains of conventional retrievers. We suspect that this is due to the next-token nature of LLM which limits its ability to retrieve meaningful sections at the lower ranks which

[14] https://cohere.com/blog/introducing-embed-v3

A. Chunking Result by Type of Chunking					
Chunking Strategy	Section/Chunk →1	Chunk/Section →1	Fail Chunk Ratio ↓	Fail Section Ratio ↓	Uncovered Section Ratio ↓
Hierarchy-awared	**1.000**	**1.000**	**0.000**	**0.000**	**0.000**
Character	3.098	1.710	0.819	0.675	0.397
Line	1.689	1.234	0.658	0.417	0.294
Recursive	1.793	1.270	0.741	0.504	0.381
B. Chunking Comparison between Hierarchy-aware and Best Naive Chunking					
Hierarchy-aware chunking	1.000	1.000	0.000	0.000	0.000
Line chunking (553 chunk size and 50 chunk overlap)	1.956	1.180	0.521	0.323	0.156

Table 16: **A.** The table showed the comparison of different naive chunking strategies compared ot our proposed hierarchy-awared chunking strategy. **B.** Using the best perform naive chunking strategy (notebly line chunking), we showed the line chunking with best parameter information loss (see §4.1) compared to hierarchy-awared chunking.



(a) NitiBench-Tax dataset.

(b) NitiBench-CCL dataset.

Figure 4: Plots showing the relationship between depth of Nitilink and retrieval performance and number of sections per query on two datasets. (a) NitiBench-Tax dataset: `Mean Diff` shows the average retrieval metric difference when increasing section depth compared to retrieval performance without NitiLink. The right plot shows the number of sections cited when resolving more reference depth. (b) NitiBench-CCL dataset.

are distant from the context and query.

L Categorized Failure Cases of Retrieval Models

To further analyze the root cause of why the model fails, we conducted error analysis on the cases where retrieval model failed to pretrieve correct relevant laws at the top ranks on both NitiBench-CCL and NitiBench-Tax. Based on manual inspections, we categorized the error cases and summarize our

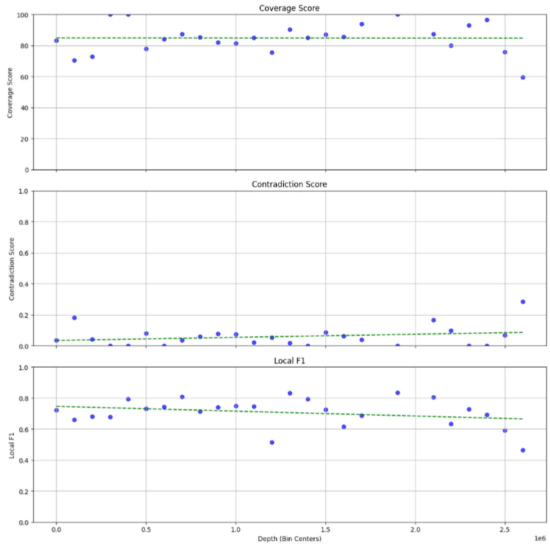


Figure 5: Plot of performance grouped by the maximum depth of relevant context in the long context

analysis in Table 18 and 19 for CCL and Tax split respectively.

M Effect of LLMs on E2E and Retrieval Performance

To better understand the gap between retrieval-based recall and end-to-end (E2E) performance, two key evaluation metrics are considered. The first one is **recall difference** (Δ Recall), which measures the gap between retriever recall and E2E recall. A lower value indicates better utilization of retrieved documents. The second metric is **hallucination rate** which indicates cases where the LLM generates correct answers without citing any relevant document, potentially relying on parametric knowledge or hallucination. The result is shown in Table 17

Claude 3.5 Sonnet consistently demonstrates the smallest recall difference across both NitiBench-CCL and NitiBench-Tax, indicating strong utiliza-

Model	**NitiBench-CCL**		**NitiBench-Tax**	
	Recall Δ	Hallucination Rate	Recall Δ	Hallucination
GPT-4o	0.058	0.069	0.100	0.100
Claude 3.5 Sonnet	0.036	0.060	0.095	0.160
Gemini 1.5 Pro	0.045	0.058	0.102	0.140
Typhoon v2-70b	0.076	0.079	0.148	0.120
Typhoon v2-8b	0.163	0.120	0.246	0.200

Table 17: Comparison of recall difference and hallucination rate across models on NitiBench-CCL and NitiBench-Tax.

tion of retrieved documents. GPT-4o achieves the lowest hallucination rate on NitiBench-Tax, suggesting high factual precision in constrained legal scenarios. In contrast, the Typhoon models exhibit significantly higher recall differences, revealing limitations in effectively leveraging retrieved evidence.

The recall gap is notably larger in the NitiBench-Tax dataset, underscoring the increased difficulty of performing accurate legal reasoning in tax law scenarios. This suggests that tasks requiring integration of hierarchical statutes and implicit logical conditions present greater challenges for generative models.

Further analysis was conducted on cases where the retriever achieved high recall but the generated response demonstrated low evidence coverage. Several recurring error patterns were observed:

- **Omission of Reasoning:** Large language models (LLMs) frequently bypass intermediate legal reasoning steps, resulting in incorrect conclusions. For instance, in cases concerning tax exemptions for income earned by a foreign spouse, models often prematurely classify the income as taxable, neglecting moral obligation clauses outlined in Section 42(28).

- **Overgeneralization of Statutes:** Especially prevalent in NitiBench-CCL, ambiguous queries often prompt models to cite multiple semantically similar provisions (e.g., Sections 18 Bis, 18 Ter, and various Petroleum Tax laws), even when only a single provision is contextually appropriate. This reflects the difficulty of legal disambiguation without explicit user clarification.

- **Overcitation:** Overcitation emerges as a leading cause of reduced E2E precision. Gemini frequently cites legally adjacent but marginally relevant sections, often triggered by superficial keyword overlaps. Claude also exhibits a broader citation strategy, particularly in NitiBench-CCL, aligning with its approach to include expansive legal references under uncertain prompts.

Error Category	**Description**	**Potential Root Cause**	**Example**
Hidden Hierarchical Information	Queries match multiple sections conveying similar meanings but located in different chapters or law codes. Without knowing the legal hierarchy, the retriever struggles to distinguish which section is contextually most relevant.	Dense retrievers lack awareness of legal, structural hierarchy (e.g., chapters, titles, codes). Legal redundancy across multiple hierarchies or acts causes confusion when embeddings treat semantically similar sections as equivalent despite different scopes.	**Section 27, Revenue Code**: Any person who fails to pay or remit taxes within the specified timeframes as stipulated in various chapters of this title concerning assessed taxes shall be subject to an additional charge of 1.5% per month or a fraction thereof on the tax amount… **Section 89/1, Revenue Code**: Any person who fails to fully pay or remit taxes within the prescribed period under this chapter shall incur an additional charge of 1.5% per month or a fraction thereof on the tax amount…
Nested Structure	Sections reference other sections without including the referenced content. Important information lies elsewhere, making it difficult for retrievers to surface full context.	Embedding models process each section in isolation and are unaware of the interdependence between referencing and referenced provisions. As a result, referenced sections are missed, and referencing ones appear insufficient.	**Section 1409, Civil and Commercial Code**: The provisions of this Code regarding the duties and liabilities of a lessee, as stipulated in Sections 552 to 555, Sections 558, 562, and 563, shall apply *mutatis mutandis*.
Missable Details	Queries include subtle legal nuances that distinguish correct from incorrect sections. The retriever often surfaces general sections that appear semantically similar but miss the key detail.	Dense embeddings focus on global semantic similarity and may underweight specific legal terms or modifiers (e.g., "secondary guarantor" vs "guarantor"). This leads to imprecise retrieval when small wording differences are legally significant.	**Question**: Can a person act as a guarantor for another guarantor? **Retrieved Section**: Section 680, Civil and Commercial Code — Suretyship is a contract in which a third party, called the guarantor… **Gold Section**: Section 682, Civil and Commercial Code — A person may act as a secondary guarantor, meaning they guarantee the obligations of the primary guarantor.
Complex Queries	Some queries implicitly require multiple reasoning steps (e.g., determining legal ownership through inference). Single-hop retrieval fails to capture these dependencies.	Dense retrievers cannot deconstruct multi-faceted questions into subcomponents. They attempt to retrieve "complete" answers but fail to retrieve steps needed for reasoning, especially when the correct answer isn't semantically similar in aggregate.	**Question**: If I buy a ring from someone and later another person claims to be the rightful owner, do I have to return the ring?

Table 18: NitiBench-CCL: Error Categories

Error Category	**Description**	**Potential Root Cause**	**Example/Elaboration**
Generic Section Retrieval Challenge	Foundational or definitional sections (e.g., terminology, tax applicability) are overlooked despite being critical for comprehensive understanding. Retrieved sections tend to be more scenario-specific and thus appear more relevant to the retriever.	Dense retrievers lack awareness of legal, structural hierarchy (e.g., chapters, titles, codes). Legal redundancy across multiple hierarchies or acts causes confusion when embeddings treat semantically similar sections as equivalent despite different scopes.	The statistics of evaluation metrics show that the section of Revenue Code with highest False Negative is section 77/2 which is a foundational section simply stating that all sales, imports, and services are subject to VAT.
Incorrect Legislation Retrieval	Sections from legislation unrelated to the specific tax scenario are retrieved due to conceptual similarity (e.g., "assessment authority" in both the Petroleum Act and Revenue Code).	Overlapping semantics between laws (e.g., penalty or tax enforcement sections) leads to false positives. This is particularly problematic when queries implicitly assume the Revenue Code without mentioning it, making it hard for retrievers to stay within scope.	It is observed from the statistics that although the ThaiLegalTax's ground truth labels span only 4 legislation, retrieved false positives originate from 21 different legislation. This mirrors the hidden hierarchical information problem observed in ThaiLegal-CCL, where similar concepts appear in different legislation. However, this problem is amplified in ThaiLegal-Tax because queries directed to the Revenue Department often omit details implicitly covered by the Revenue Code's scope.
Incorrect Tax Type Retrieval	Model confuses the applicable tax (e.g., retrieves corporate tax sections for personal income tax scenarios), especially in complex cross-border or employment-related queries.	Keyword cues in queries (e.g., "company," "foreign income") can shift embeddings toward corporate or VAT contexts. Without tax-type disambiguation, the retriever struggles to recognize the correct interpretation when multiple tax regimes are involved.	A query about the tax obligations of an employee in Thailand receiving income from both a subsidiary and its parent company (a personal income tax question) should retrieve Sections 41, 48, 50, and 56 of the Revenue Code, which addresses personal income tax, withholding obligations, and calculating tax on foreign income. However, the model instead retrieves sections related to corporate and export taxes. This likely stems from keywords like "company", "corporate", and "foreign" influencing the query embedding, shifting its focus away from personal income tax.

Table 19: Error categories and examples observed in NitiBench-Tax dataset retrieval tasks.

NitiBench-CCL Dataset

Top-K	Model	HR/Recall@k	MRR@k
k=1	BM25	.481	.481
	JINA V2	.681	.681
	JINA V3	.587	.587
	NV-Embed V1	.492	.492
	BGE-M3	.700	.700
	Human-Finetuned BGE-M3	**.735**	**.735**
	Auto-Finetuned BGE-M3	.731	.731
	Cohere	.676	.676
k=5	BM25	.658	.548
	JINA V2	.852	.750
	JINA V3	.821	.681
	NV-Embed V1	.713	.579
	BGE-M3	.880	.773
	Human-Finetuned BGE-M3	**.906**	**.805**
	Auto-Finetuned BGE-M3	.900	.800
	Cohere	.870	.754
k=10	BM25	.715	.556
	JINA V2	.889	.755
	JINA V3	.875	.688
	NV-Embed V1	.776	.587
	BGE-M3	.919	.778
	Human-Finetuned BGE-M3	**.938**	**.809**
	Auto-Finetuned BGE-M3	.934	.804
	Cohere	.912	.760

NitiBench-Tax Dataset

Top-K	Model	HR@k	Multi HR@k	Recall@k	MRR@k	Multi MRR@k
k=1	BM25	.220	.080	.070	.220	.118
	JINA V2	.140	.040	.035	.140	.068
	JINA V3	.400	.100	.134	.400	.203
	NV-Embed V1	.100	.020	.028	.100	.035
	BGE-M3	.500	.140	.176	.500	.269
	Human-Finetuned BGE-M3	.480	.140	.176	.480	.255
	Auto-Finetuned BGE-M3	**.520**	**.160**	**.190**	**.520**	**.281**
	Cohere	.340	.100	.127	.340	.179
k=5	BM25	.480	.120	.211	.318	.171
	JINA V2	.200	.080	.070	.165	.085
	JINA V3	.720	**.260**	**.324**	.508	.297
	NV-Embed V1	.200	.020	.077	.126	.050
	BGE-M3	.720	.240	.338	.580	**.337**
	Human-Finetuned BGE-M3	**.740**	.220	.331	.565	.320
	Auto-Finetuned BGE-M3	.700	.200	.310	**.587**	.329
	Cohere	.620	.200	.268	.447	.256
k=10	BM25	.540	.160	.282	.327	.183
	JINA V2	.240	.100	.099	.171	.091
	JINA V3	**.840**	.340	.444	.524	.311
	NV-Embed V1	.220	.040	.085	.128	.052
	BGE-M3	.820	**.360**	**.472**	.593	**.354**
	Human-Finetuned BGE-M3	.800	.280	.437	.574	.333
	Auto-Finetuned BGE-M3	.780	.260	.423	**.600**	.345
	Cohere	.680	.200	.352	.454	.263

Table 20: Retrieval Evaluation Results on NitiBench-CCL Dataset and NitiBench-Tax Dataset with hierarchy-aware chunking.

LLM	Referencer	Retriever Recall (↑)	E2E Recall (↑)	E2E Precision (↑)	E2E F1 (↑)	Coverage (↑)	Contradiction (↓)
NitiBench-Tax Dataset							
grok-4	No Ref	0.437	0.393	0.404	0.398	**63.0**	0.38
gpt-5			0.409	**0.427**	0.418	57.0	**0.36**
claude-4.1-opus			0.442	0.382	0.410	55.0	0.44
gemini-2.5-pro			**0.567**	0.390	**0.462**	59.0	0.42

Table 21: Preliminary benchmark scores for recent LLMs, evaluated exclusively on the NitiBench-Tax dataset with No Ref reference setting. These results offer a targeted snapshot of state-of-the-art performance on tax law, complementing the main findings in Table 3.