JBE-QA: Japanese Bar Exam QA Dataset for Assessing Legal Domain Knowledge

Zhihan Cao[1], Fumihito Nishino[2], Hiroaki Yamada[1],
Nguyen Ha Thanh[2,3], Yusuke Miyao[4], Ken Satoh[2]

[1] Institute of Science Tokyo, Japan [2] ROIS-DS, Center for Juris-informatics, Japan
[3] National Institute of Informatics, Japan [4] University of Tokyo, Japan
cao.z.c8a7@m.isct.ac.jp nishino@nii.ac.jp, yamada@comp.isct.ac.jp
nguyenhathanh@nii.ac.jp yusuke@is.s.u-tokyo.ac.jp ksatoh@nii.ac.jp

Abstract

We introduce JBE-QA, a Japanese Bar Exam Question–Answering dataset to evaluate large language models' legal knowledge. Derived from the multiple-choice (*tantō-shiki*) section of the Japanese bar exam (2015–2024), JBE-QA provides the first comprehensive benchmark for Japanese legal-domain evaluation of LLMs. It covers the Civil Code, the Penal Code, and the Constitution, extending beyond the Civil Code focus of prior Japanese resources. Each question is decomposed into independent true/false judgments with structured contextual fields. The dataset contains 3,464 items with balanced labels. We evaluate 26 LLMs, including proprietary, open-weight, Japanese-specialised, and reasoning models. Our results show that proprietary models with reasoning enabled perform best, and the Constitution questions are generally easier than the Civil Code or the Penal Code questions.

Keywords: Japanese Bar Exam, Legal QA, Japanese law, LLM evaluation, benchmark, dataset

1. Introduction

Legal practice relies heavily on the individual professional's expertise and experience. This expert-dependency raises the need for legal information processing, which, for example, helps retrieve legal documents efficiently and analyse their argumentative structures (Nguyen et al., 2024; Vuong et al., 2023). In this way, legal information processing reduces the expert-dependency in legal practice and improves access to legal information for non-expert users. Currently, Large Language Models (LLMs) are widely applied to legal information processing (Nguyen et al., 2025a). Given the high-stakes nature of legal information processing, LLMs must have accurate knowledge in the legal domain to be reliable.

Previous researchers have developed resources that evaluate the knowledge quality of LLMs. Legal-Bench (Guha et al., 2023) is a multi-task benchmark focused on legal reasoning, covering subjects such as the Constitution, the Penal Code, and the Civil Code of the United States. MultiEURLEX (Chalkidis et al., 2021) is a multilingual corpus of EU laws for document topic classification, covering laws of transportation and agriculture. JEC-QA (Zhong et al., 2020) is a large-scale question-answering dataset derived from the Chinese National Judicial Examination. It contains questions regarding diverse subjects such as the Constitution, the Penal Code, and the Civil Code.

Nevertheless, the availability, as well as the scope, of Japanese legal resources are limited. Only a few publicly available datasets exist, most

of which focus on the Civil Code of Japan. For example, the COLIEE dataset (Goebel et al., 2024) involves information retrieval and entailment tasks concerning the Civil Code. Choi et al. (2023) implemented binary legal questions to evaluate LLM's performance in the Japanese legal domain, but they only released a subset for the Civil Code questions. The Japanese Tort-case Dataset (Yamada et al., 2024) evaluates the ability of models to predict judgments in tort cases from the Civil Code. In summary, the existing Japanese resources have their limitations in coverage: they mainly focus on the Civil Code, whereas few target the Penal Code or the Constitution.

Three major subjects of law, the Civil Code, the Penal Code, and the Constitution, differ in functions and positions. The Civil Code, as a core of private laws, regulates legal interactions between private individuals. However, since legal issues also arise between the public and the private, the public laws, exemplified by the Penal Code or the Constitution, are equally essential for understanding the law. Particularly, the Constitution is important as it is the supreme law governing all the laws. Given the above, all three major subjects of law must be covered in an evaluation resource to establish a comprehensive evaluation of LLMs' legal knowledge. Yet, there is no currently available resource that fulfills this requirement, leading to a partial and insufficient understanding of LLMs' legal knowledge.

To fill this gap, we construct a new comprehensive dataset, Japanese Bar Exam QA (JBE-QA). JBE-QA dataset targets the Civil Code, the Pe-

nal Code, and the Constitution at the same time and hence has a larger scope compared to existing evaluation resources in the Japanese legal domain. In this way, our JBE-QA dataset enables a comprehensive legal knowledge evaluation. We establish baseline performance on the JBE-QA dataset by evaluating 26 large language models, including proprietary, open-weight, generic multilingual, Japanese-specialised, and reasoning-oriented models. This baseline demonstrates the coverage of Japanese legal knowledge in current LLMs and serves as a benchmark for future model improvements. Our dataset is available online.

2. Dataset Construction

Our dataset is derived from the Japanese Bar Examination (JBE)[1], specifically from the multiple-choice type questions, *tantō-shiki* test. All the data are in the Japanese language.

2.1. Japanese Bar Exam

JBE is a national examination that grants the legal qualifications required to become a judge, prosecutor, or attorney in Japan. The JBE consists of two tests: the *tantō-shiki* test and the *ronbun-shiki* test, where the former is a multiple-choice test, and the latter is an essay-writing test. The *tantō-shiki* test assesses whether an examinee has the legal knowledge and reasoning ability required to become a legal professional. The *ronbun-shiki* test is intended to evaluate whether the examinee has the skills in legal analysis, organisation, and argumentation writing that are necessary for legal practice. Both tests include a wide range of problems from multiple subjects, including the Civil Code, the Penal Code, and the Constitution.

2.2. Question Design

Our JBE-QA dataset is based on the *tantō-shiki* test because it focuses more on legal knowledge itself than on the application of legal knowledge. This aligns with our evaluation objective of comprehensively assessing LLMs' understanding of legal knowledge. Furthermore, its question format is choice-based, making it suitable for automated evaluation. In the original *tantō-shiki* test, a question is usually a set of statements about a legal topic, each of which is either true or false[2]. For a question, multiple options are provided, and each option is a list of binary values that indicate the truth of every statement in the question. Examinees need

to pick the option that correctly represents the truth conditions of all statements in the question.

On the left-hand side of Figure 1, we show a question regarding the Constitution. Examinees are given multiple-choice options numbered from 1 to 8, each representing a different combination of truth values. In the example question, as all the statements are incorrect, examinees should select option 8.

In our dataset, we simplify the *tantō-shiki* test by dividing each question into multiple binary classification problems. A model under evaluation only needs to determine the truth of each statement one at a time, rather than the combinations of truths of a set of statements. This allows us to interpret the result in a more fine-grained manner and align with the former practice in COLIEE (Goebel et al., 2024) as well. In the example, we split the question into three binary classification tasks corresponding to statements A, B, and C, as shown on the right-hand side of Figure 1.

2.3. Data Collection and Preprocessing

Past exam PDFs are publicly available on the website of the Ministry of Justice of Japan[3]. We downloaded the PDFs of the past exams between 2015 and 2024. The PDFs were converted into structured XML files for preprocessing. Automated scripts were applied to normalise formats and detect common extraction errors, followed by targeted manual review and correction where necessary.

Some of the questions from the original bar exam could not be formatted as binary true/false items. We removed such questions, resulting in our final dataset containing minor differences from the original exams. In total, 52 questions were excluded: 46 from the Penal Code, 5 from the Constitution, and 1 from the Civil Code.

2.4. Data Structure and Quality Assurance

To convert the original multiple-choice questions into binary questions, it is necessary to segment and then structure the question text.

All the original questions have instructional text, which provides explicit guidance on the basis for answering them (shown in blue fonts in Figure 1). We extract this part as `instruction` field. Another element that always exists in the original question is statement text shown in red fonts in Figure 1. An LLM must determine the truth of the statement text. We hold them as `question` field in our dataset. `Theme` field, shown in yellow fonts in Figure 1, gives scope or topics of the questions.

---

[1] 司法試験, *Shihō Shiken*

[2] There are minor cases where the question has a more complicated structure.

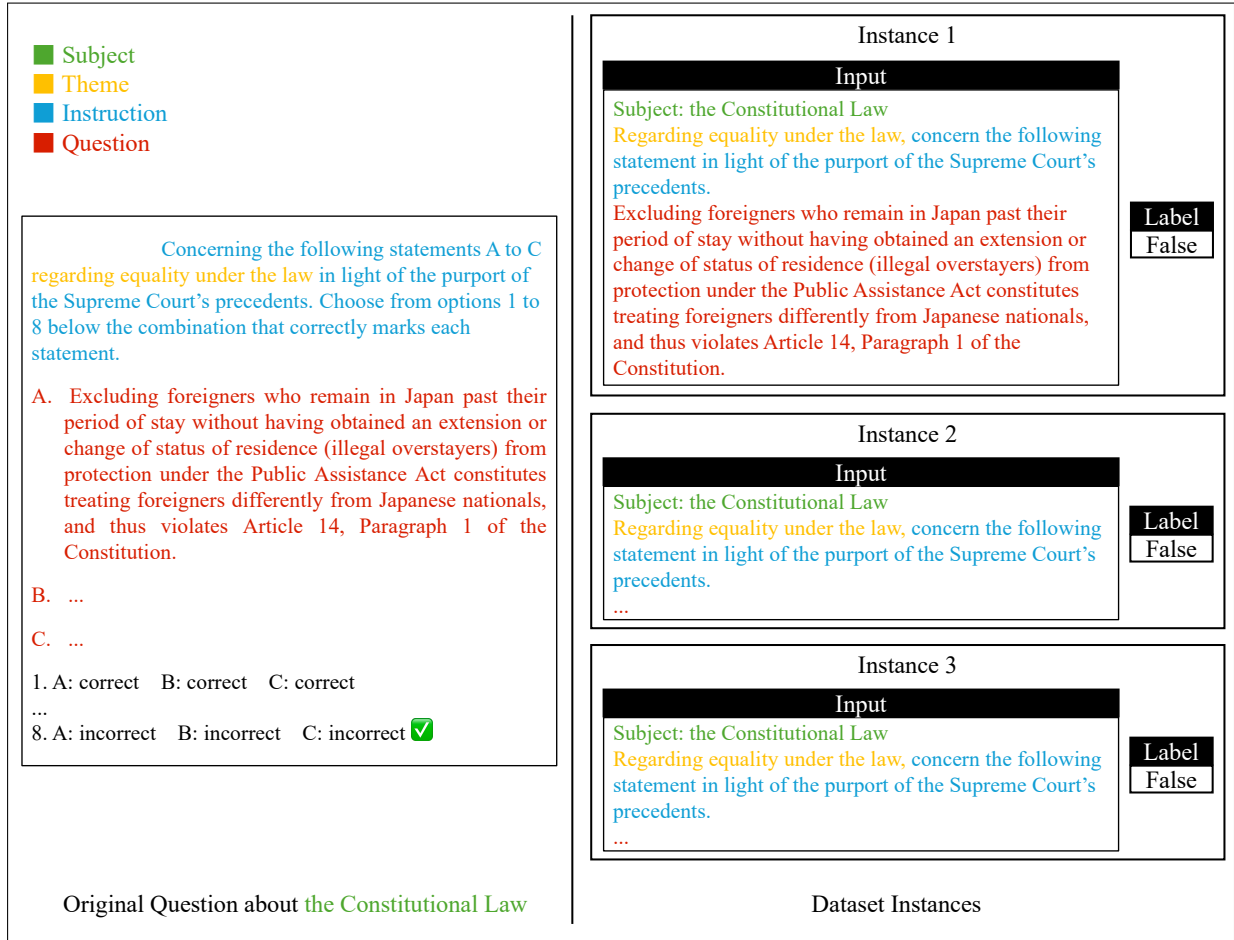[3] https://www.moj.go.jp/barexam.html

Figure 1: English translation of an example of the Japanese bar exam *tantō-shiki* test (left) and its format in the JBE-QA dataset (right). Note that not all fields introduced in Section 2.4 are in this example.

Some of the original questions have auxiliary text providing context or additional materials. For example, there is a type of question that their `instruction` refers to a long description of a case presented separately from the instruction. We extract such text as `lead_in` field in our dataset. Also, some questions have clarifications or special remarks that make them simpler or solvable. An example is the expression "Ignore damages, and enforcement costs." in a question about identifying the correct amount of money to be distributed to each stakeholder of a real estate. `remark` field holds them.

Building on this structure, each instance in the dataset contains the following fields:

- `id`: Unique identifier for each question.

- `year`: Examination year in Japanese era format.

- `subject`: Legal subject in English.

- `subject_jp`: Legal subject in Japanese.

- `instruction`: Clear instructions for answering in Japanese.

- `question`: Question text in Japanese.

- `label`: Original label (Y for True, N for False).

- `answer`: Standardised answer (True/False).

- `theme`: legal topic or theme in Japanese. Optional.

- `lead_in`: Auxiliary text provided separately from instruction or question. Optional.

- `remark`: Clarifications or supplementary text. Optional.

To ensure the quality and integrity of the dataset, we performed a thorough manual review to identify and correct any mismatches between questions and their gold labels that had occurred during the initial automated extraction. This post-processing step was vital for improving the reliability of the dataset as a benchmark for evaluating LLMs.

2.5. Dataset Statistics

The dataset consists of 3,464 question-answer pairs. Table 1 shows the distribution of questions across the three core legal subjects. This distribution reflects the emphasis on the Civil Code in

Subject	Count	Percentage
The Civil Code	1,998	57.7%
The Penal Code	811	23.4%
The Constitution	655	18.9%

Table 1: Distribution of questions subjects

the Japanese Bar Examination. The dataset is balanced in terms of answer distribution, with 52.4% of the instances having a "False" label and 47.6% having a "True" label.

3. Baseline Experiment

Each instance in the JBE-QA dataset represents a binary classification problem. We instruct an LLM under evaluation to only output a binary truth value as the prediction for every instance (c.f. Section 3.2). However, some models may fail to follow the instruction, resulting in non-binary outputs. In such cases, the prediction is set to 0 (False) by default. In order to quantify the frequency of such cases, we compute the faithfulness to instruction (hereafter, faithfulness score), defined as the ratio of instances where the model produces a binary output.

We use the F1 score as the metric of performance, which is standard for binary classification. Each model is evaluated in zero-shot and four-shot settings. In order to ensure the comparability of results, we exclude instances used as exemplars for the four-shot setting while calculating the results. Consequently, each model's score under a given metric is averaged over $3464 - 4 = 3460$ instances.

3.1. Models

We evaluate various types of models, including both proprietary and open-weight ones. For proprietary models, we consider models from OpenAI (OpenAI, 2023) and Anthropic (Anthropic, 2024). For the OpenAI models, we employ GPT-4.1, GPT-4o, GPT-5, o3, and o4-mini[4]. Among them, GPT-5, o3, and o4-mini are reasoning models. For the Anthropic models, we use four Claude models: Opus-3, Opus-4.1, Sonnet-4, Sonnet-4.5, and Haiku-3.5[5]. Among them, Claude Opus-4.1 and Sonnet-4 & 4.5 support reasoning ("extended thinking") (Anthropic, 2025), and we evaluate these three models both with and without reasoning enabled.

For open-weight models, we consider both generic multilingual and Japanese-specialised models in order to investigate whether general-domain adaptation for Japanese leads to better performance in the Japanese legal domain as well. All the models selected are instruction-tuned and have more than 15 billion parameters. For generic models, we employ Qwen 2.5-32B & 72B (Qwen et al., 2025), GPT-OSS-20B & 120B (OpenAI, 2025), Gemma 3-12B & 27B (Gemma Team, 2025), Llama 3.1 (Meta, 2024a) & 3.3 (Meta, 2024b)[6].

The Japanese-specialised models include ABEJA-V2 (ABEJA, 2025), Swallow-3.1 & 3.3 (Fujii et al., 2024; Okazaki et al., 2024; Ma et al., 2025), and two LLM-jp-3.1 models (National Institute of Informatics, 2025), a 13B dense one and a 104B mixture-of-experts one[7]. ABEJA-V2 is a 32B Qwen 2.5 model fine-tuned on a Japanese corpus. Swallow-3.1 & 3.3 are based on Llama-3.1-70B and Llama-3.3-70B, respectively, with continual pre-training on Japanese data. Unlike the models above that are based on generic multilingual models, the LLM-jp-3.1 series is built upon a Japanese-native LLM.

In total, there are 26 models evaluated, considering Opus-4.1, Sonnet-4, and Sonnet-4.5 with and without reasoning enabled as six different models.

3.2. Experimental Settings

System Prompt We instruct models using the following system prompt for each model. The English translation is given below.

> 以下の法律に関する問題を解答せよ。理由や説明は不要。「正しい」と判断した時に1を、「誤り」と判断したときに0を出力せよ。出力は必ず1または0のいずれかの整数値のみとせよ。
> (Answer the following legal question. No reason or explanation is required. Output 1 if you judge the statement to be correct, and 0 if incorrect. The output must be only an integer, either 1 or 0.)

For llm-jp-3.1 models, which do not allow modifying the system prompt by default, we add the same instruction at the beginning of the user input.

---

[4] gpt-4.1-2025-04-14, gpt-4o-2024-11-20, gpt-5-2025-08-07, o3-2025-04-16, o4-mini-2025-04-16 in order.

[5] claude-3-opus-20240229, claude-opus-4-1-20250805, claude-sonnet-4-20250514, claude-sonnet-4-5-20250929, claude-3-5-haiku-20241022 in order.

[6] Qwen2.5-32B-Instruct, Qwen2.5-72B-Instruct, gpt-oss-20b, gpt-oss-120b, gemma-3-12b-it, gemma-3-27b-it, Llama-3.1-70B-Instruct, Llama-3.3-70B-Instruct in order.

[7] ABEJA-Qwen2.5-32b-Japanese-v0.1, Llama-3.1-Swallow-70B-Instruct-v0.3, Llama-3.3-Swallow-70B-Instruct-v0.4, llm-jp-3.1-13b-instruct4, llm-jp-3.1-8x13b-instruct4 in order.

Four-shot Learning Setting   Four instances are sampled from the training set and used as exemplars across all model evaluation experiments. Two are randomly sampled from positive instances, and the other two from negative instances.

Question format   Using the data fields defined in JBE-QA, we formatted questions according to the following rules[8]. All questions are given in Japanese to the models.

The first line specifies the subject of the question (the `subject_jp` field), such as the green text "Subject: The Constitution" in Figure 1.

The next line indicates the theme of the question (given in the `theme` field), if it exists. In the right-hand side of Figure 1, the yellow text "Regarding equality under the law" specifies the subject.

Some questions include background information (stored in the `lead_in` field). If so, such information is attached after the theme line.

A question description (the `instruction` field) and the statement (the `question` field) are presented in order. In the example, the `instruction` field is "concern the following statement in light of the purport of the Supreme Court's precedents".

Finally, if the question contains additional annotations or clarifications (the `remark` field), they are appended at the end.

Hyper-parameters   We set the temperature to 0 when evaluating non-reasoning models. This forces the model to predict the token with the highest likelihood at each time step, making generation deterministic. Non-reasoning models' maximum output length is set to 1,000 tokens. Note that we expect the models to output either 1 or 0 if they are faithful to our instruction. Thus, 1,000 tokens are long enough for our experiments. For open reasoning models, we use the temperature of 1, and for proprietary reasoning models, we use their default temperature values[9]. We limit the maximum output length to one quarter of the allowed maximum. This is in order to ensure the model under evaluation has enough tokens for sufficient reasoning. All evaluations are conducted once per model.

4.   Baseline Results

Table 2 presents the F1 and Faithfulness scores on the whole dataset, under zero- and four-shot settings, grouped by whether a model is open (O), is Japanese-specialised (J), and supports reasoning (R).

---

[8]The formatter script is available online.

[9]They are usually 1. Some models, for example GPT-5 and o3, do not support adjustment of temperature parameter.

Overall, proprietary models show better performance than open-weight models on the JBE-QA dataset. Proprietary models achieve F1 scores ranging from 0.602 to 0.861, except outliers Haiku-3.5 and Sonnet-4.5. Compared with the proprietary models, open-weight models show lower scores, with F1 scores ranging from 0.320 to 0.731.

The low F1 scores of Haiku-3.5 and Sonnet-4.5 stem from their low faithfulness scores. Most models are able to follow the instruction, given the majority of faithfulness scores exceed 0.990. However, Haiku-3.5 and Sonnet-4.5 have a faithfulness score of 0.259 and 0.027, respectively. A common pattern in the outputs of Haiku-3.5 and Sonnet-4.5 is that they provide reasons after the prediction, even though we instructed them to output only a binary value. For example, "1. Explanation: According to the position of the case law, this case constitutes the crime of evidence destruction.". When a model's output is not a binary value as instructed, its prediction is set to 0 by default (c.f. Section 3). This results in an increase of false negatives and, consequently, a decrease in F1 score.

For proprietary models, providing exemplars generally improves their performance. This trend is particularly noticeable for Haiku-3.5 and Sonnet-4.5, whose F1 scores increase by more than 0.500 in the four-shot setting. In contrast, eight out of thirteen open-weight models do not show higher scores in the four-shot setting than in the zero-shot setting. For example, Llama-3.3 has an F1 score of 0.620 in the four-shot setting, which is 0.058 lower than in the zero-shot setting.

For LLM-jp-3.1 models, exposure to exemplars even substantially decreases their performance. The F1 score of LLM-jp-3.1-13B drops from around 0.582 in the zero-shot setting to around 0.244 in the four-shot setting. For LLM-jp-3.1-8x13B, it decreases from 0.495 to 0.320. This decline is attributed to the models' tendency to generate content that is similar to the provided exemplars. An inspection of the LLM-jp 13B outputs shows that it tends to answer the input question in binary value first. Subsequently, it generates content regarding cash and extortion, which exactly matches the topic of the last exemplar. Consequently, many of its predictions are set to 0, leading to a large drop in faithfulness scores and hence a lower F1 score.

In short, while exemplars might provide clues for proprietary models, they could instead distract open-weight models from solving the task. This difference may stem from the high-quality and large-scale corpora used to pretrain and fine-tune proprietary models. Such data exposure likely helps these models better capture the semantic content of exemplars and follow the intended format, rather than being misled by their superficial information.

Proprietary reasoning models outperform their

O	J	R	Model	F1		Faithfulness	
				Zero-shot	Four-shot	Zero-shot	Four-shot
×	×	×	GPT-4.1	0.724	0.731	0.989	0.995
			GPT-4o-11	0.708	0.731	0.997	0.995
			Sonnet 4	0.694	0.738	0.895	1.000
			Opus 3	0.686	0.708	1.000	1.000
			Opus 4.1	0.602	0.799	0.648	1.000
			Haiku 3.5	0.148	0.666	0.259	1.000
			Sonnet 4.5	0.055	0.751	0.027	1.000
×	×	✓	Opus 4.1 (w/ Reasoning)	0.814	0.861	0.873	1.000
			GPT-5	0.794	0.783	1.000	1.000
			Sonnet 4 (w/ Reasoning)	0.780	0.776	0.992	1.000
			o3	0.769	0.762	1.000	1.000
			o4-mini	0.672	0.673	1.000	1.000
			Sonnet 4.5 (w/ Reasoning)	0.077	0.828	0.040	0.999
✓	×	×	Qwen2.5-72B	0.707	0.716	1.000	1.000
			Llama-3.3-70B	0.678	0.620	1.000	0.999
			Llama-3.1-70B	0.674	0.672	1.000	1.000
			Gemma-3-27B	0.652	0.627	1.000	1.000
			Gemma-3-12B	0.637	0.585	1.000	1.000
			Qwen2.5-32B	0.622	0.645	0.999	1.000
✓	×	✓	GPT-OSS-120B	0.632	0.617	0.998	1.000
			GPT-OSS-20B	0.601	0.590	1.000	0.994
✓	✓	×	Swallow-3.1-70B	0.698	0.698	1.000	1.000
			Swallow-3.3-70B	0.692	0.731	1.000	1.000
			ABEJA-V2-32B	0.687	0.694	0.992	1.000
			LLM-jp-3.1-13B	0.582	0.244	1.000	0.202
			LLM-jp-3.1-8x13B	0.495	0.320	1.000	0.836

Table 2: F1 scores and Faithfulness scores across models, zero- and four-shot settings, and dataset splits. O indicates whether the model is open-weight, J indicates whether the model is Japanese-specialised, and R indicates whether the model is a reasoning model. The models are sorted by their F1 scores in the zero-shot setting within groups sharing the same O, J, and R values.

non-reasoning counterparts. For reasoning models, the F1 scores range from 0.077 to 0.814 in the zero-shot setting and from 0.673 to 0.861 in the four-shot setting. For non-reasoning models, the performance ranges from 0.055 to 0.724 and from 0.666 to 0.799 under zero-shot and four-shot settings, respectively. However, for open-weight models, the performance gain brought by reasoning is not as strong as for proprietary models. This can be observed from the fact that the GPT-OSS models do not always outperform the open non-reasoning models.

The Japanese specialisation leads to a marginal improvement under the zero-shot setting. Swallow-3.1 and Swallow-3.3, which are derived from Llama-3.1 and 3.3, respectively, via continued pretraining on Japanese corpora, show an advantage of less than 0.03. ABEJA-V2 outperforms its base model, Qwen2.5-32B, by 0.065. The advantage of Japanese specialisation becomes most evident for Llama-3.3 under the four-shot setting. Swallow-3.3 outperforms Llama-3.3 by 0.111, but for other models, the improvement is less than 0.050.

The performance of the models trained on Japanese corpora from scratch is unsatisfactory. The F1 scores of LLM-jp-3.1 models remain lower, staying less than 0.600 in the zero-shot setting and less than 0.350 under the four-shot setting. These scores are close to, or even below, the F1 score expected from random guessing, which is 0.488, given our task is a binary classification with 47.6% positive instances.

4.1. Performance on Subjects

Table 3 shows the F1 scores for each subject. In both zero-shot and four-shot settings, the performance on the Constitution is always the highest or the second highest. For example, Opus-4.1 with reasoning reaches an F1 score above 0.900 for the Constitution in both four-shot and zero-shot settings. All models evaluated have relatively good knowledge of the Constitution.

By contrast, across models, the Civil Code and the Penal Code are consistently the subjects that models struggle with, regardless of model family

O	J	R	Model	Zero-shot			Four-shot		
				Cvl	Cst	Pen	Cvl	Cst	Pen
✕	✕	✕	GPT-4.1	0.722	0.739	0.719	0.729	0.758	0.715
			GPT-4o-11	0.719	0.720	0.668	0.740	0.750	0.687
			Haiku 3.5	0.060	0.238	0.282	0.645	0.724	0.675
			Opus 3	0.664	0.783	0.656	0.698	0.790	0.658
			Opus 4.1	0.617	0.733	0.405	0.795	0.876	0.741
			Sonnet 4	0.668	0.826	0.636	0.712	0.861	0.692
			Sonnet 4.5	0.028	0.184	0.011	0.733	0.872	0.685
✕	✕	✓	GPT-5	0.779	0.845	0.791	0.767	0.846	0.771
			Opus 4.1 (w/ Reasoning)	0.816	0.905	0.715	0.853	0.918	0.831
			Sonnet 4 (w/ Reasoning)	0.757	0.847	0.784	0.762	0.835	0.766
			Sonnet 4.5 (w/ Reasoning)	0.016	0.284	0.045	0.821	0.889	0.796
			o3	0.757	0.831	0.746	0.731	0.843	0.776
			o4-mini	0.661	0.718	0.663	0.648	0.740	0.686
✓	✕	✕	Gemma-3-12B	0.632	0.676	0.613	0.561	0.675	0.560
			Gemma-3-27B	0.632	0.712	0.647	0.599	0.698	0.633
			Llama-3.1-70B	0.680	0.680	0.651	0.667	0.710	0.651
			Llama-3.3-70B	0.678	0.697	0.660	0.565	0.735	0.650
			Qwen2.5-32B	0.581	0.710	0.650	0.608	0.727	0.667
			Qwen2.5-72B	0.695	0.746	0.707	0.707	0.750	0.710
✓	✕	✓	GPT-OSS-120B	0.612	0.701	0.627	0.611	0.666	0.594
			GPT-OSS-20B	0.590	0.655	0.583	0.569	0.636	0.606
✓	✓	✕	ABEJA-V2-32B	0.671	0.748	0.673	0.673	0.773	0.682
			LLM-jp-3.1-13B	0.577	0.619	0.563	0.096	0.471	0.343
			LLM-jp-3.1-8x13B	0.452	0.595	0.513	0.254	0.512	0.307
			Swallow-3.1-70B	0.700	0.711	0.681	0.677	0.751	0.710
			Swallow-3.3-70B	0.699	0.698	0.666	0.725	0.772	0.711

Table 3: F1 scores on every subject across models, zero- and four-shot settings and dataset splits. O, J, and R share the meaning with tables above. Cvl, Cst, and Pen represent the Civil Code, the Constitution, and the Penal Code, respectively.

or zero- and four-shot settings. For the zero-shot setting, 11 out of 26 models show the poorest performance on the Civil Code, whereas 15 on the Penal Code. This pattern does not change largely for the four-shot setting: 14 models show the poorest performance on the Civil Code, and 12 on the Penal Code.

Comparing the statistics under zero- and four-shot settings, the subject where models perform the worst changes only marginally, regardless of whether exemplars are provided. In contrast, the reasoning capability of models contributed to their performance. Among seven proprietary non-reasoning models, six perform worst on the Penal Code, whereas among six proprietary reasoning models, four perform the worst on the Civil Code. Reasoning generally improves model performance, but it may benefit different subjects to varying degrees.

4.2. Case Study

Among all instances, there is a particularly difficult one that none of the models is able to solve,

regardless of whether it is under a zero-shot or few-shot setting. We present the instance in English translation below.

> Is the following statement concerning the Crimes of Arson and Fire Caused through Negligence correct or not?
> A person *A* lived alone in a house that he owned. The house was covered by fire insurance. Intending to obtain the insurance payout on the house fraudulently, he set fire to his own house, completely burning it down and thereby endangering the public. In this case, *A* is guilty of the crime of Arson of Uninhabited Buildings belonging to another person.

The statement in the question is about the crime of "Arson of Uninhabited Buildings belonging to another person" (Art. 109 of the Penal Code). The correct answer to the question is True according to both the interpretation of the precedents and the related articles.

First, the phrase "Uninhabited Buildings" in this case is not used in its literal sense. Instead, its

interpretation has been established in the precedents. Specifically, "Uninhabited Buildings" refers to buildings that are not being inhabited by anyone other than the offender. In this case, because the inhabitant *A* is the very person who set the building on fire, this building is considered "Uninhabited".

Second, Art. 115 of the Penal Code defines a special case regarding the "Arson of Uninhabited Buildings belonging to another person". If the owner sets fire to their own building and the building is insured, the owner is considered to be an offender of another person's building. Thus, in this case *A* is considered to set fire to "buildings belonging to another person".

If a model lacks precise knowledge of related articles in the Penal Code and their judicial interpretation established in the precedents and instead relies only on the superficial information of the phrases "Uninhabited" and "belonging to another person", it might produce an incorrect judgment.

We inspect the reasoning part of the best-performing model Opus-4 (w/ Reasoning). In its reasoning outputs, Opus-4 raises the following reasons: "*A*'s house was his own property, not that of another person", and "Since *A* lived there alone, it was an inhabited building, not an uninhabited one", Similar reasoning patterns can be observed in other models as well. Therefore, the evaluated models are influenced by superficial information and might not properly possess the knowledge of the related article and precedents.

5. Related Work

There are different benchmarks, from focusing on single tasks in specific jurisdictions to employing multiple tasks, languages, and legal systems, reflecting the growing needs of computational solutions for the legal domain.

For English resources, LexGLUE (Chalkidis et al., 2022), provided a suite of tasks for legal language understanding. This was followed by Legal-Bench (Guha et al., 2023), a collaboratively built benchmark with 162 tasks focused on legal reasoning across the Constitution, the Penal Code, and the Civil Code of the United States. Moreover, there are datasets focused on specific tasks like legal judgment prediction, with datasets such as PILOT (Cao et al., 2024) and ClassActionPrediction (Semo et al., 2022).

In Europe, MultiEURLEX (Chalkidis et al., 2021) provided a multilingual corpus of EU laws for document topic classification, covering 23 languages. LEXTREME (Niklaus et al., 2023) expanded on this with 11 datasets covering 24 languages, providing a multi-task benchmark for the legal domain. Other notable European resources included EUR-Lex-Sum for legal document summarisation (Aumiller

et al., 2022) and benchmarks based on Swiss legal document (Rasiah et al., 2023).

Asian legal systems have also seen a surge in benchmark development. For Chinese, JEC-QA (Zhong et al., 2020) is a large-scale question-answering dataset from the National Judicial Examination. More recent and comprehensive benchmarks include LawBench (Fei et al., 2023) with 20 tasks, LexEval (Li et al., 2024) with 23 tasks, and LAiW (Dai et al., 2025). For Indian law, IL-TUR (Joshi et al., 2024) provided a multilingual benchmark, and Nyayaanumana (Nigam et al., 2025) is a large judgment prediction dataset. In Korea, LBOX OPEN (Hwang et al., 2022) and KBL (Kimyeeun et al., 2024) are prominent multi-task benchmarks. Southeast Asian languages are also represented, with benchmarks for Thai (NitiBench, Akarajaradwong et al., 2025), Vietnamese (VLQA, Nguyen et al., 2025b), and Indonesian (IndoLER, Yulianti et al., 2024).

In Japan, there are a few benchmark datasets available for the legal domain. COLIEE (Goebel et al., 2024) employed the subset of questions from the *tantō-shiki* test. They utilised the Civil Code questions and designed their task as a textual entailment task and information retrieval. Choi et al. (2023) also employed the *tantō-shiki* test to evaluate the performance of GPT-3 (Brown et al., 2020), GPT-3.5-turbo, and GPT-4 (OpenAI, 2023) in the Japanese legal domain. They tasked the models to solve the multiple-choice questions as-is in the *tantō-shiki* test. They also provided binary questions converted from the *tantō-shiki* similar to our dataset, but only available for the Civil Code. More recently, the Japanese Tort-case Dataset (JTD) (Yamada et al., 2024) provided a dataset for Japanese Legal Judgment Prediction (LJP), focusing on tort cases from the Civil Code of Japan. However, these datasets are limited in scope, primarily focusing on the Civil Code. Our work introduces the first comprehensive benchmark that covers not only the Civil Code but also the Penal Code and the Constitution, addressing a significant gap in resources for evaluating LLMs on Japanese legal texts.

6. Conclusion

We introduce JBE-QA, a dataset for evaluating LLMs' legal knowledge. It covers the Civil Code, the Penal Code, and the Constitution, extending beyond the Civil Code focus of the previous Japanese legal resources, and hence enabling a comprehensive legal knowledge evaluation. We benchmark 26 models, including proprietary, open-weight, Japanese-specialised, and reasoning models, under zero-shot and four-shot settings. Hence, we establish the baseline of legal knowledge quality of the current models. The results show that reason-

ing and proprietary models perform best, Japanese specialisation improves few-shot performance, and the Constitution is easier than the Civil Code or the Penal Code, highlighting the possible directions of future improvements.

7. Ethics Statement

We believe that this dataset does not contain any significant ethical concerns. Our source of the dataset is an official archive of the past Japanese bar exam, and it does not contain any private information or confidential information. Currently, there are no feasible use cases for this dataset that can involve potential harm or ethical issues.

8. Limitations

Our dataset primarily focuses on the fundamental legal knowledge of the Japanese legal system using *tantō-shiki* questions. The *tantō-shiki* questions require relatively fewer reasoning steps in order to apply the knowledge to solve the questions, compared with *ronbun-shiki* questions. In the practical situation, more intensive legal reasoning is required to apply the legal knowledge correctly to a longer context. To evaluate such higher-level reasoning and knowledge application, *ronbun-shiki* questions would be a good device. The difficulty of evaluating the *ronbun-shiki* questions, even with human experts, restricts the direct implementation of them as a benchmark task; however, it would be an interesting future direction.

Another limitation of the current version of this dataset is that the questions are not automatically updated even if the relevant laws are revised. Thus, there is a risk that the gold labels in the dataset might not align with future versions of laws. Developing an automatic update system for questions affected by revised laws would be an ideal solution.

9. Acknowledgement

10. Bibliographical References

ABEJA. 2025. Abeja-qwen2.5-32b-japanese-v0.1: A japanese language model based on qwen2.5-32b-instruct.

Pawitsapak Akarajaradwong, Pirat Pothavorn, Chompakorn Chaksangchaichot, Panuthep Tasawong, Thitiwat Nopparatbundit, Keerakiat Pratai, and Sarana Nutanong. 2025. Nitibench: A comprehensive study of llm framework capabilities for thai legal question answering. *arXiv preprint arXiv:2502.10868*.

Anthropic. 2024. Claude 3: Opus, sonnet, and haiku.

Anthropic. 2025. Building with extended thinking.

Dennis Aumiller, Ashish Chouhan, and Michael Gertz. 2022. EUR-lex-sum: A multi- and cross-lingual dataset for long-form summarization in the legal domain. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 7626–7639, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners. In *Proceedings of the 34th International Conference on Neural Information Processing Systems*, NIPS '20, Red Hook, NY, USA. Curran Associates Inc.

Lang Cao, Zifeng Wang, Cao Xiao, and Jimeng Sun. 2024. Pilot: Legal case outcome prediction with case law. In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 609–621.

Ilias Chalkidis, Manos Fergadiotis, and Ion Androutsopoulos. 2021. MultiEURLEX - a multilingual and multi-label legal document classification dataset for zero-shot cross-lingual transfer. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 6974–6996, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Ilias Chalkidis, Abhik Jana, Dirk Hartung, Michael Bommarito, Ion Androutsopoulos, Daniel Katz, and Nikolaos Aletras. 2022. LexGLUE: A benchmark dataset for legal language understanding in

English. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 4310–4330, Dublin, Ireland. Association for Computational Linguistics.

Jungmin Choi, Jungo Kasai, and Keisuke Sakaguchi. 2023. Evaluating gpt in japanese bar examination: Insights and limitations. *Jxiv preprint*.

Yongfu Dai, Duanyu Feng, Jimin Huang, Haochen Jia, Qianqian Xie, Yifang Zhang, Weiguang Han, Wei Tian, and Hao Wang. 2025. Laiw: A chinese legal large language models benchmark. In *Proceedings of the 31st International Conference on Computational Linguistics*, pages 10738–10766.

Zhiwei Fei, Xiaoyu Shen, D. Zhu, Fengzhe Zhou, Zhuo Han, Songyang Zhang, Kai Chen, Zongwen Shen, and Jidong Ge. 2023. Lawbench: Benchmarking legal knowledge of large language models. *ArXiv*, abs/2309.16289.

Kazuki Fujii, Taishi Nakamura, Mengsay Loem, Hiroki Iida, Masanari Ohi, Kakeru Hattori, Hirai Shota, Sakae Mizuki, Rio Yokota, and Naoaki Okazaki. 2024. Continual pre-training for cross-lingual llm adaptation: Enhancing japanese language capabilities. In *Proceedings of the First Conference on Language Modeling*, COLM, page (to appear), University of Pennsylvania, USA.

Gemma Team. 2025. Gemma 3 technical report. *arXiv preprint arXiv:2503.19786*.

Randy Goebel, Yoshinobu Kano, Mi-Young Kim, Juliano Rabelo, Ken Satoh, and Masaharu Yoshioka. 2024. Overview and discussion of the competition on legal information extraction/entailment (COLIEE) 2023. *The Review of Socionetwork Strategies*, 18(1):27–47.

Neel Guha, Julian Nyarko, Daniel Ho, Christopher Ré, Adam Chilton, Aditya K, Alex Chohlas-Wood, Austin Peters, Brandon Waldon, Daniel Rockmore, Diego Zambrano, Dmitry Talisman, Enam Hoque, Faiz Surani, Frank Fagan, Galit Sarfaty, Gregory Dickinson, Haggai Porat, Jason Hegland, Jessica Wu, Joe Nudell, Joel Niklaus, John Nay, Jonathan Choi, Kevin Tobia, Margaret Hagan, Megan Ma, Michael Livermore, Nikon Rasumov-Rahe, Nils Holzenberger, Noam Kolt, Peter Henderson, Sean Rehaag, Sharad Goel, Shang Gao, Spencer Williams, Sunny Gandhi, Tom Zur, Varun Iyer, and Zehua Li. 2023. Legalbench: A collaboratively built benchmark for measuring legal reasoning in large language models. In *Advances in Neural Information Processing Systems*, volume 36, pages 44123–44279. Curran Associates, Inc.

Wonseok Hwang, Dongjun Lee, Kyoungyeon Cho, Hanuhl Lee, and Minjoon Seo. 2022. A multitask benchmark for korean legal language understanding and judgement prediction. *Advances in Neural Information Processing Systems*, 35:32537–32551.

Abhinav Joshi, Shounak Paul, Akshat Sharma, Pawan Goyal, Saptarshi Ghosh, and Ashutosh Modi. 2024. Il-tur: Benchmark for indian legal text understanding and reasoning. *Unknown Journal*, pages 11460–11499.

Kimyeeun Kimyeeun, Choi Youngrok, Eunkyung Choi, JinHwan Choi, Hai Park, and Wonseok Hwang. 2024. Developing a pragmatic benchmark for assessing korean legal language understanding in large language models. In *Findings of the Association for Computational Linguistics: EMNLP 2024*, pages 5573–5595.

Haitao Li, You Chen, Qingyao Ai, Yueyue Wu, Ruizhe Zhang, and Yiqun Liu. 2024. Lexeval: A comprehensive chinese legal benchmark for evaluating large language models. *ArXiv*, abs/2409.20288.

Youmi Ma, Sakae Mizuki, Kazuki Fujii, Taishi Nakamura, Masanari Ohi, Hinari Shimada, Taihei Shiotani, Koshiro Saito, Koki Maeda, Kakeru Hattori, Takumi Okamoto, Shigeki Ishida, Rio Yokota, Hiroya Takamura, and Naoaki Okazaki. 2025. Building instruction-tuning datasets from human-written instructions with open-weight large language models. *arXiv preprint arXiv:2503.23714*.

Meta. 2024a. Introducing llama 3.1: Our most capable models to date.

Meta. 2024b. Llama 3.3 70b instruct: A multilingual instruction-tuned large language model.

National Institute of Informatics. 2025. Llm-jp 3.1 series: Open japanese language models.

Ha Thanh Nguyen, Wachara Fungwacharakorn, May Myo Zin, Randy Goebel, Francesca Toni, Kostas Stathis, and Ken Satoh. 2025a. Llms for legal reasoning: A unified framework and future perspectives. *Computer Law & Security Review*, 58:106165.

Ha-Thanh Nguyen, Manh-Kien Phi, Xuan-Bach Ngo, Vu Tran, Le-Minh Nguyen, and Minh-Phuong Tu. 2024. Attentive deep neural networks for legal document retrieval. *Artificial Intelligence and Law*, 32(1):57–86.

Tan-Minh Nguyen, Hoang-Trung Nguyen, Trong-Khoi Dao, Xuan-Hieu Phan, Ha-Thanh Nguyen, and Thi-Hai-Yen Vuong. 2025b. Vlqa: The

first comprehensive, large, and high-quality vietnamese dataset for legal question answering. *arXiv preprint arXiv:2507.19995*.

Shubham Kumar Nigam, Deepak Patnaik Balaramamahanthi, Shivam Mishra, Noel Shallum, Kripabandhu Ghosh, and Arnab Bhattacharya. 2025. Nyayaanumana and inlegalllama: The largest indian legal judgment prediction dataset and specialized language model for enhanced decision analysis. In *Proceedings of the 31st International Conference on Computational Linguistics*, pages 11135–11160.

Joel Niklaus, Veton Matoshi, Pooja Rani, Andrea Galassi, Matthias Sturmer, and Ilias Chalkidis. 2023. Lextreme: A multi-lingual and multi-task benchmark for the legal domain.

Naoaki Okazaki, Kakeru Hattori, Hirai Shota, Hiroki Iida, Masanari Ohi, Kazuki Fujii, Taishi Nakamura, Mengsay Loem, Rio Yokota, and Sakae Mizuki. 2024. Building a large japanese web corpus for large language models. In *Proceedings of the First Conference on Language Modeling*, COLM, page (to appear), University of Pennsylvania, USA.

OpenAI. 2023. Gpt-4 technical report.

OpenAI. 2025. gpt-oss-120b & gpt-oss-20b model card. *arXiv preprint arXiv:2508.10925*.

Qwen, An Yang, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chengyuan Li, Dayiheng Liu, Fei Huang, Haoran Wei, Huan Lin, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Yang, Jiaxi Yang, Jingren Zhou, Junyang Lin, Kai Dang, Keming Lu, Keqin Bao, Kexin Yang, Le Yu, Mei Li, Mingfeng Xue, Pei Zhang, Qin Zhu, Rui Men, Runji Lin, Tianhao Li, Tianyi Tang, Tingyu Xia, Xingzhang Ren, Xuancheng Ren, Yang Fan, Yang Su, Yichang Zhang, Yu Wan, Yuqiong Liu, Zeyu Cui, Zhenru Zhang, and Zihan Qiu. 2025. Qwen2.5 technical report. *arXiv preprint arXiv:2412.15115*.

Vishvaksenan Rasiah, Ronja Stern, Veton Matoshi, Matthias Sturmer, Ilias Chalkidis, Daniel Ho, and Joel Niklaus. 2023. One law, many languages: Benchmarking multilingual legal reasoning for judicial support.

Gil Semo, Dor Bernsohn, Ben Hagag, Gila Hayat, and Joel Niklaus. 2022. Classactionprediction: A challenging benchmark for legal judgment prediction of class action cases in the us.

Yen Thi-Hai Vuong, Quan Minh Bui, Ha-Thanh Nguyen, Thi-Thu-Trang Nguyen, Vu Tran, Xuan-Hieu Phan, Ken Satoh, and Le-Minh Nguyen. 2023. Sm-bert-cr: a deep learning approach for case law retrieval with supporting model. *Artificial Intelligence and Law*, 31(3):601–628.

Hiroaki Yamada, Takenobu Tokunaga, Ryutaro Ohara, Akira Tokutsu, Keisuke Takeshita, and Mihoko Sumida. 2024. Japanese tort-case dataset for rationale-supported legal judgment prediction. *Artificial Intelligence and Law*, pages 1–25.

Evi Yulianti, Naradhipa Bhary, Jafar Abdurrohman, Fariz Wahyuzan Dwitilas, Eka Qadri Nuranti, and Husna Sarirah Husin. 2024. Named entity recognition on indonesian legal documents: a dataset and study using transformer-based models. *International Journal of Electrical & Computer Engineering (2088-8708)*, 14(5).

Haoxi Zhong, Chaojun Xiao, Cunchao Tu, Tianyang Zhang, Zhiyuan Liu, and Maosong Sun. 2020. JEC-QA: A legal-domain question answering dataset. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 9701–9708.