# Impact of Large Language Models on Generating Software Specifications

Danning Xie\* Purdue University West Lafayette, IN, USA xie342@purdue.edu Byungwoo Yoo\* UNIST Ulsan, South Korea captainnemo9292@unist.ac.kr Nan Jiang Purdue University West Lafayette, IN, USA jiang719@purdue.edu Mijung Kim<sup>†</sup>
UNIST
Ulsan, South Korea
mijungk@unist.ac.kr

Lin Tan
Purdue University
West Lafayette, IN, USA
lintan@purdue.edu

Xiangyu Zhang Purdue University West Lafayette, IN, USA xyzhang@cs.purdue.edu Judy S. Lee
IBM Chief Analytics Office
Armonk, NY, USA
leesj@us.ibm.com

# **ABSTRACT**

Software specifications are essential for ensuring the reliability of software systems. Existing specification extraction approaches. however, suffer from limited generalizability and require manual efforts. We study the effectiveness of Large Language Models (LLMs) in generating software specifications from software documentation, utilizing Few-Shot Learning (FSL) to enable LLMs to generalize from a small number of examples. We compare the performance of LLMs with FSL to that of state-of-the-art specification extraction techniques and study the impact of prompt construction strategies on LLM performance. In addition, we conduct a comprehensive analysis of their symptoms and root causes of the failures to understand the pros and cons of LLMs and existing approaches. We also compare 11 LLMs' performance, cost, and response time for generating software specifications. Our findings include that (1) the best performing LLM outperforms existing approaches by 9.1–13.7% with a few similar examples, (2) the two dominant root causes combined (ineffective prompts and missing domain knowledge) result in 57-60% of LLM failures, and (3) most of the 11 LLMs achieve better or comparable performance compared to traditional techniques. Our study offers valuable insights for future research to improve specification generation including better examples in the LLM prompt and adding domain knowledge.

### 1 INTRODUCTION

Accurate and comprehensive software specifications are essential for ensuring the correctness, dependability, and quality of software systems [8, 20, 51, 56]. Common software specifications include pre- and post-conditions to a target function that describes the constraints of input parameters and the expected behaviors or output values, which are often required or crucial for the generation of effective test cases and test oracles, symbolic execution, or abnormal behavior identification [8, 9, 12, 55, 56, 59].

Numerous approaches have been proposed to advance automation in extracting specifications from software texts (e.g., documents or comments), including rule-based methods [8, 52, 56], ML-based methods [41, 51], search-based methods [59], etc. For example, Jdoctor [8] leverages patterns, lexical, and semantic matching to translate code comments into machine-readable specifications of

pre-/post-conditions, which enables automated test generation that leads to fewer false alarms and the discovery of more defects. Doc-Ter [56] automatically constructs rules that map sentence patterns to Deep Learning specific constraints that are used to guide test input generation and reveal unknown bugs in DL libraries. Several other attempts have been made to further improve these processes in various domains [32, 41, 59, 60]. However, the majority of existing work is domain-specific relying on heuristics [8, 52] or a large amount of manually annotated data [56, 59]. This reliance makes it challenging to generalize these approaches to other domains.

With the emergence of Large Language Models [11, 17, 43], which have been pre-trained on a tremendous amount of documents and source code [16, 18, 36, 58], they have been applied to various Software Engineering (SE) tasks such as code generation [14, 16, 28, 36, 58] and program repair [22]. These models have demonstrated competitive performance compared to traditional approaches [5, 18, 22, 36, 58]. Consequently, a research question arises: how do LLMs perform in generating software specifications automatically from software documentation?

We hence conduct a study to evaluate the capabilities of LLMs in extracting software specifications compared to existing approaches. First, we use *Few-Shot Learning* [13, 26, 45, 47, 54], a technique that enables LLMs to generalize from a limited number of examples, as labeled data in software specification extraction is scarce. We start with a basic prompt construction method to provide examples for FSL, which helps LLMs learn how to generate specifications from software texts. We leverage datasets from the previous specification extraction research, to evaluate and compare the performance of LLMs with FSL with state-of-the-art specification extraction techniques.

Second, to explore the potential of LLMs with FSL for extracting specifications, we evaluate and compare different prompt construction strategies in terms of their impact on the performance of LLMs for specification extraction. Such prompt construction strategies include selecting examples randomly and selecting examples that are semantically close to a given specification generation task.

Third, we investigate the symptoms and root causes of failures of both LLMs and existing approaches, providing an in-depth analysis of their respective pros and cons, which can help identify challenges for improvement and guide future research.

Finally, we compare various LLMs in terms of their performance, cost, and response time for generating software specifications. We

<sup>\*</sup>The first two authors contributed equally to this paper.

<sup>&</sup>lt;sup>†</sup>Corresponding author

conduct experiments using 11 LLMs of varying designs and sizes. The evaluation allows us to determine the trade-offs among LLMs and identify the most suitable and economical models for this task. This paper makes the following key contributions:

- The first study that examines the effectiveness of LLMs in generating software specifications from the documentation.
  - Finding 1: With 10-60 randomly selected examples, LLMs outperform state-of-the-art specification extraction techniques by 2.0-11.3%, achieving 93% accuracy and 81.1% F1.
- (2) A study of LLM prompt construction strategies on different example retrieval methods.
  - Finding 2: With a more sophisticated prompt construction method, the performance gap between LLMs and traditional approaches is enlarged to 9.1–13.7%.
- (3) A comprehensive analysis that studies failing cases of LLMs and existing approaches, including symptoms and root causes, in order to understand the pros and cons of these methods.
  - Finding 3: Traditional approaches are more likely to generate no specifications, while the failing cases of LLM approaches are dominant with ill-formed or incomplete ones.
  - Finding 4: The two prevalent root causes combined (ineffective prompts and missing domain knowledge) result in 57-60% of LLM failures.
  - Finding 5: LLMs suffer from ineffective prompts and wrong focuses, causing 50–73% unique LLM failures, i.e., LLMs fail but traditional methods succeed, while rule-based methods' insufficient or incorrect rules cause 73–93% of unique failures.
- (4) A study of 11 LLMs on their performance, cost, and response time for generating software specifications.
  - Finding 6: Most LLMs achieve better or comparable performance, with quick response times, to traditional techniques.
  - Finding 7: Codex is the top model for generating specifications, with high performance, \$0 cost, long prompt support, and quick responses.
  - Finding 8: Codex's strong performance makes GPT-3 Davinci less desirable due to size and cost. Economical alternatives GPT-3 Curie and GPT-3.5 have lower performance. CodeGen and BLOOM are good open-source alternatives.

## 2 BACKGROUND

Large Language Models Large Language Models (LLMs) are deep learning models pre-trained on a large corpus that contains natural language texts and programming language source code. LLMs learn general knowledge of natural languages (e.g., grammar including text syntaxes and semantics) and programming languages (e.g., code syntaxes and semantics) from the pre-training tasks such as masked span prediction [17, 27] and next token prediction [7, 11, 42, 43, 53].

While LLMs demonstrate strong performance on pre-training tasks, they are less effective in downstream tasks such as text summarization and specification extraction as they are different from the pre-trained tasks and domain-specific. To adapt and enhance LLMs for downstream tasks, common techniques include fine-tuning [17, 22, 42, 44] and few-shot learning [11, 43]. Fine-tuning typically requires additional training data, such as labeled

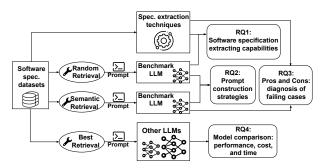


Figure 1: Study Overview

document-specification pairs while few-shot learning usually requires only a limited number of training instances.

**Few-Shot Learning (FSL)** Few-shot learning (FSL) is crucial for enhancing pre-trained LLMs' comprehension and performance in downstream tasks, especially when limited labeled data is available, as in [11, 45, 47, 54]. In this work, we focus on in-context few-shot learning [11, 57], where LLM weights remain unchanged. FSL involves a small amount of labeled data into the LLM input as prompts, guiding LLMs to effectively learn the specific task without modifying their weights or architecture.

Consider a dataset  $D = \{(x_i, y_i)\}_{i=1}^{I}$ , where x represents the context and y denotes the expected completion. In our study, x corresponds to the document or comments while y refers to the target software specifications. For each data point  $(x_{target}, y_{target})$  in D, we first select K indices, denoted by S. Then,  $\{(x_k, y_k)\}_{k \in S}$  are K(i.e., |S|) examples of input context  $x_k$  and their corresponding ground-truth completions  $y_k$ .

There are multiple ways to sample the examples; for instance, one can split the dataset into  $D_{train}$  and  $D_{test}$ , and only select examples from  $D_{train}$  for the target in  $D_{test}$ . In our study, to utilize as many cases as possible and explore the upper limit of FSL, we use leave-one-out cross-validation [10, 21, 33], where we select the K examples from all other |I|-1 data points in D except for the target itself. These examples are integrated into the prompt  $P=\{(x_k,y_k)\}_{k\in S}+x_{target}$ , where the target context is appended to the end of the prompt. Subsequently, the LLMs generate the completion  $y_{out}$  for the target context. This output is then compared against the ground-truth completion,  $y_{target}$ .

# 3 STUDY SETUP

Fig. 1 presents an overview of our study. We collect available datasets from previous specification extraction work, containing software documents and comments and the corresponding ground-truth specifications. We then answer four research questions (RQs):

**RQ1:** How do LLMs compare with existing rule-based approaches to extracting software specifications? We evaluate the specification extraction capabilities of LLMs in comparison to existing approaches, applying the benchmark LLM to the collected datasets For LLMs, we use a basic prompt construction strategy random retrieval to construct prompts with random examples (Section 3.2.1). These prompts coach the LLMs to extract specifications from software texts by examples.

RQ2: How do prompt construction strategies affect the performance of the LLM approaches? We compare the performance of

Function signature	isNullOrEmpty(java.lang.String string)
Javadoc comment	@return true if the string is null or is the empty string
Specification	string==null  string.isEmpty() -methodResultID==true

Figure 2: Example data point from Jdoctor dataset

Function signature	<pre>tf.image.extract_glimpse(input,size,offsets,)</pre>
Document description	<pre>input: A Tensor of type `float32'. A 4-D float tensor of shape `[batch_size,height,width,channels] .</pre>
Specifications	dtype: float32 structure: tensor shape: [batch_size, height, width, channels] ndim: 4 range: Null enum: Null

Figure 3: Example data point from DocTer dataset

different prompt construction strategies, i.e., *Random Retrieval* and *Semantic Retrieval*. Semantic retrieval selects examples based on semantic similarity to the target context (discussed in Section 3.2.2).

**RQ3:** What are the pros and cons of LLMs and traditional approaches? To provide better insights into the pros and cons of different approaches and shed light on future research, we conduct a comparative diagnosis of failing cases. In particular, we sample a set of cases that an LLM approach succeeds while the traditional approach fails and vice versa. We also summarize the symptoms and root causes of these failures, especially for the LLM approaches.

RQ4: How do different LLMs compare in terms of performance, cost, and response time for extracting software specifications? To assess performance, cost, and response time, we conduct experiments on this task with 11 LLMs of different sizes, designs, and so forth. We employ the best-performing prompt construction strategy ("Best Retrieval" in the figure) based on the results of RQ2.

# 3.1 Existing Specification Extraction and Data

We compare with two state-of-the-art specification extraction approaches, Jdoctor [8] and DocTer [56], which are rule-based. The comparison is conducted on their datasets. Both datasets consist of annotated comments or documents with associated specifications. To avoid confusion, we use the terms Jdoctor-data and DocTer-data to refer to the datasets, while Jdoctor and DocTer refer to the two approaches.

Table 1 presents the number of data points in each dataset in column "#Annotation", listing the number of document-specification pairs annotated for Jdoctor-data, and the parameter-specification pairs from each library of DocTer-data.

**Jdoctor-data** contains pre-/post-conditions in the form of executable procedure specifications written as Java expressions translated from corresponding Javadoc comments. Fig. 2 presents an example. The comment is a Javadoc with @return tag, describing the post-condition of the isNullOrEmpty function. The figure illustrates the specification, with corresponding parts highlighted in matching colors. In addition to the @return tag, the dataset contains data points with @param and @throws tags.

**Jdoctor** translates Javadoc comments into specifications using a combined approach of pattern, lexical, and semantic matching. It first identifies (subject, predicate) pairs in sentences. Fig. 2 presents an example, where the phrase "the string is null" contains such a pair with the subject "the string" and predicate "is null". It then

```
\begin{array}{lll} \text{Signature:} & < x_i - \text{signature} > \\ \text{Javadoc comment:} & < x_j - \text{comment} > \\ \text{Condition:} & < y_j > \\ \dots & & \\ \text{Signature:} & < x_k - \text{signature} > \\ \text{Javadoc comment:} & < x_k - \text{signature} > \\ \text{Javadoc comment:} & < x_k - \text{comment} > \\ \text{Condition:} & < y_k > \\ \text{Signature:} & < x_k - \text{signature} > \\ \text{Description:} & < x_k - \text{param.} > - < x_k - \text{descp.} > \\ \text{Constraints:} & < y_j > \\ \text{Signature:} & < x_k - \text{signature} > \\ \text{Description:} & < x_k - \text{param.} > - < x_k - \text{descp.} > \\ \text{Constraints:} & < y_k > \\ \text{Signature:} & & \text{Signature:} & \\ \text{Signature:} & & \text{Signature:} & \\ \text{Description:} & & & \text{signature:} \\ \text{Constraints:} & & & \text{Constraints:} & \\ \text{Constraints:} & & & \text{Constraints:} & \\ \text{Constraints:} & & & \text{Constraints:} \\ \text{Constraints:} & & & & \\ \text{Constraints:} & & & \\ \text{Constraints:} & & & \\ \text{Constraints:} &
```

(a) Idoctor-data

(b) DocTer-data

Figure 4: Prompt structures with target highlighted in orange.

**Table 1: Software Specification Datasets** 

Dataset	Tag Type / Library	#Annotation
	Precond @param	183
Jdoctor [8]	Normal postcond @return	79
	Exceptional postcond @throws	412
	Total	674
	TensorFlow	948
DocTer [56]	PyTorch	424
	MXNet	1,324
	Total	2,696

translates these pairs into executable procedures by applying manually defined heuristics (e.g., the phrase "is null" to Java expression ==null). Next, it applies lexical matching to match a subject or a predicate to the corresponding code element based on lexical similarity (e.g., matching "the string" to input parameter string). Finally, it uses semantic matching to process meanings such as negation.

**DocTer-data** contains DL-specific specifications from the API documents of DL libraries. Fig. 3 shows an example data point. DocTer categorizes specifications into four groups: *dtype* for data types, *structure* for data structures, *shape* for the parameter's shape or the number of dimensions (ndim), and *valid value* refers to the set of valid values (enum) or the valid range (range).

**DocTer** automatically constructs rules that map syntactic patterns of API descriptions to specifications using a portion of annotated data. These rules are then applied to API documents to extract parameter specifications. For instance, DocTer automatically constructs a rule that maps the syntactic pattern "of type D\_TYPE" to the *dtype* specification, where "D\_TYPE" is a placeholder for any data type keyword. By applying this rule to the description of parameter input "A Tensor of type float32" (shown in Fig. 3), the *dtype* specification "float32" is extracted.

#### 3.2 Specification Generation with LLMs and FSL

To extract specifications using an LLM, we construct prompts that contain examples to coach the LLM, i.e., via few-shot learning. As discussed in Section 2, to construct an FSL prompt for the given target context  $x_{target}$ , we select K examples (i.e.,  $\{(x_k, y_k)\}_{k \in S}$ ) from the dataset and append  $x_{target}$  to the end. Fig. 4 presents example prompts for Jdoctor-data and DocTer-data.

(1) **Prompt Construction:** In the prompt for Jdoctor-data, as shown in Fig. 4a, each of the K examples includes the function signature  $\langle x_k$ -signature $\rangle$ , the Javadoc comment  $\langle x_k$ -comment $\rangle$ , and the corresponding annotated condition  $\langle y_k \rangle$ . Then, the target  $x_{target}$  is appended to the end of the prompt (highlighted in orange).

Signature: min(float[] array)

Javadoc: @param array a nonempty array of float values

Annotation: (array.length==0)==false
Generated: array.length>0

Figure 5: Equivalent Conditions: A Jdoctor Example with Semantically Correct LLM Completion

Similarly, the prompt for DocTer-data (Fig. 4b) includes the function signature  $\langle x_k$ -signature $\rangle$ , the document description  $\langle x_k$ -param. $\rangle$  -  $\langle x_k$ -descp. $\rangle$ , where  $\langle x_k$ -descp. $\rangle$  is the corresponding document description for the parameter  $\langle x_k$ -param. $\rangle$ , and the annotated constraints ( $\langle y_k \rangle$ ).

We treat the three tag types from Jdoctor-data (Table 1) and the DocTer-data from three libraries as separate datasets. For example, for a target of <code>@param</code> tag, we only select K examples from the other 182 data points of <code>@param</code> tag, excluding itself. Similarly, in DocTer-data, for a target, we select examples from the same library, excluding itself. We study two commonly used strategies to choose the K examples:  $random\ retrieval$  and  $semantic\ retrieval$ .

- 3.2.1 Random Retrieval. The random retrieval strategy is randomly selecting K examples from the training dataset, excluding itself, i.e.,  $D \setminus \{(x_{target}, y_{target})\}$ . For example, when conducting experiments on a target from Jdoctor-data context (i.e., target), with K = 20, we randomly select 20 instances from the Jdoctor-data excluding the target itself and use the 20 instances as examples in the prompt.
- 3.2.2 Semantic Retrieval (SR). The SR strategy aims to select examples semantically close to the target context. Previous studies [30, 48] show that SR significantly improves the performance of FSL compared with random retrieval. BERT-based models are more effective compared to traditional methods, such as TF-IDF, in improving the performance of FSL, according to previous studies [30, 48]. We choose RoBERTa [31] as the SR retrieval model due to its outstanding performance on the Semantic Textual Similarity (STS) dataset [46]. We do not study the impact of different retrieval models since previous research suggests that the differences in results for different language models are small [50].
- (2) Post-Processing of LLM Output: For Jdoctor-data, LLMgenerated completions may be semantically correct, albeit not identical to the annotations provided in the dataset. Fig. 5 illustrates an example of a Jdoctor-data data point in the evaluation set, including the function signature, Javadoc comment, annotated specification (in yellow), and the specification generated by LLM (in blue). The annotated and generated specifications, although not identical, both convey the requirement that the variable array must be a nonempty Array. An automatic script that checks for a perfect match would label this as an incorrect result. Such equivalent but syntactically different specifications frequently occur in LLM results and pose a challenge for automatic assessment, especially when domain-specific knowledge is needed (e.g., the length of an array can never be negative). Therefore, we manually inspect the generated completions for Jdoctor-data that deviate from the annotation and report both raw accuracy automatically calculated by the script and the final accuracy after manual correction. Here, two of the authors conducted the manual correction. Any disagreements are resolved by a third author.

Table 2: Studied Large Language Models. The table presents the number of parameters (#Param, \* denoting estimates), token limit (maximum input length), price per 1,000 tokens (if applicable), and open-source status. BLOOM's 1,000-token limit pertains to the API, not the model.

Model	#Param	Token limit	Price (per 1K)	Open-source?
Codex [16]	Davinci (12B*)	8000	=	×
CDT 2 [11]	Davinci (175B*)	4000	\$0.02	Х
GPT-3 [11]	Curie (Unknown)	2048	\$0.002	×
GPT3.5 [38]	Turbo (Unknown)	4096	0.002	Х
BLOOM [49]	176B	1000*	-	1
CodeGen [36]	16B, 6B, 2B, 350M	2048	=	1
InCoder [18]	6B, 1B	2048	=	<b>✓</b>

## 3.3 Studied Large Language Models

Table 2 summarizes 11 large language models (LLMs) from six series that we study in this paper, including the best generic LLMs, code-specific LLMs, and open-sourced LLMs. We select GPT-3.5 over ChatGPT, as the changes made for ChatGPT focus on conversations [37].

Codex [16] starts from a GPT-3 checkpoint with 12 billion parameters, which has been pre-trained on a 45 TB natural language corpus and 159 GB source code dataset collected from GitHub. The pre-training task focuses on the next token prediction, which enables the model to perform well in various software engineering tasks, such as code completion, code summarization, and more [16]. We study Codex by accessing OpenAI's API through model code-davinci-002.

*GPT-3* [11] shares the same architecture and pre-training task as Codex. GPT-3 is pre-trained only on text data from sources like Wikipedia and digital books. We study the two best GPT-3 models: GPT-3-Davinci (175B), the largest and most capable GPT-3 model, and GPT-3-Curie with unknown size, the second-best model according to OpenAI. We access them via OpenAI's API through model text-davinci-003 and text-curie-001.

*GPT-3.5* [38] is the most powerful LLM for dialogue at the time of the experiment. It is initially pre-trained using the same techniques as GPT-3, and is subsequentially fine-tuned with "Reinforcement Learning from Human Feedback (RLHF)" [25, 34, 40, 61] technique. We access it via OpenAI's API through the model gpt-3.5-turbo, which is the primary backend model powering ChatGPT [37].

**BLOOM** [49] is an open-sourced model similar to GPT-3 in structure. BLOOM is pre-trained on a 1.61 TB corpus containing both natural language and source code data [49]. We select BLOOM-176B, which has 176 billion parameters. We study this model by accessing its Hugging Face API [3].

CodeGen [36] is a transformer-based LLM for program synthesis, pre-trained on THEPILE [19], BigQuery [2], and BigPython [36]. We study CodeGen-350M/2B/6B/16B-Multi models, which are pre-trained on THEPILE and BigQuery and expected to generalize well to both Jdoctor-data and DocTer-data. We also examine CodeGen-350M/2B/6B/16B-Mono pre-trained additionally on BigPython, providing an advantage for DocTer-data's Python-related tasks.

*InCoder* [18] is an LLM based on the XGLM [29] architecture, employing code infilling as its pre-training task. The pre-training

data contains 57 GB of natural language text and 159 GB of source code collected from platforms like GitHub and StackOverflow. We study the InCoder-1B and InCoder-6B models.

We run CodeGen and InCoder locally with 4 Nvidia RTX A5000 GPUs with 24GB memory.

#### 3.4 Benchmark LLM

We choose to use Codex as the benchmark LLM for the study of RQ1, RQ2, and RQ3 (Fig. 1), as Codex is free and supports more input tokens than all other models (Table 2), enabling a wide range of experimental settings, such as different numbers of examples in the prompt. In addition, Codex is specifically designed for translating natural language to code, which aligns well with our task of translating natural language comments and documents to machine-readable specifications. After identifying the best prompt construction strategies ("Best Retrieval" in Fig. 1) using Codex, we apply it to all other LLMs listed in Table 2 for the study of RQ4.

#### 4 EXPERIMENTAL SETTINGS

## 4.1 Model settings

As per our experimental design, we truncate examples from the beginning of the prompts to fit the token limit of each model (as shown in Table 2). If the median number of tokens in the prompts exceeds the limit, we skip that experiment. For instance, we skip the experiment for Jdoctor-data when K=60 for BLOOM (with a token limit of 1,000) since the median number of tokens in the prompts is 3,737. To calculate the number of tokens in each prompt, we use the AutoTokenizer [1]. To provide comprehensive results, we run the benchmark model (Codex) for RQ1 and RQ2 in all settings.

We follow the recommended practice [4] of using the separator \n\n##\n\n between examples in the prompts. For the generative models, we use the same separator as the stopword. We set the models' temperature to 0 for minimal randomness and to reflect the models' most confident answers. The max\_tokens parameter is set to 100 for Jdoctor-data and 200 for DocTer-data, larger than the number of tokens in the longest completion in each dataset.

## 4.2 Accuracy and F1 Metrics

To evaluate the correctness of the generated specifications, we employ the accuracy metric for the generated specifications for Jdoctor-data. As LLMs under consideration inherently generate a specification for all given Javadoc comments, standard metrics such as precision and recall do not provide additional information in this experiment setting. We define the accuracy as  $Accuracy = \frac{C}{|D|}$ , where C is the number of accurately generated specifications, and |D| is the total number of specifications annotated in D.

For DocTer-data, we use precision, recall, and F1 metrics to evaluate the generated results for each specification category (e.g., dtype). For category t, let  $C_t$  be the number of correctly generated specifications,  $N_t$  be the total number of annotated specifications in the dataset for category t (i.e.,  $D_t$ ), and  $G_t$  denote the number of generated specifications for category t. We define precision as  $P_t = \frac{C_t}{G_t}$ , recall as  $R_t = \frac{C_t}{N_t}$ , and F1 score as  $F_t = 2 \cdot \frac{P_t \cdot R_t}{P_t + R_t}$ . We report the overall precision, recall, and F1 across all four categories (dtype, structure, shape, and valid value) for each library (e.g., TensorFlow),

Table 3: Comparison of Codex with random prompt construction and Jdoctor: Accuracy (%) for Extracting Pre- and Post-conditions from Javadoc Comments

A 1 77	T/	, @param		@	@return		@throws		Overall	
Approach	трргоасн к	Raw	Processed	Raw	Processed	Raw	Processed	Raw	Processed	
Jdoctor	-	96.7	96.7	63.9	63.9	78.5	78.5	81.7	81.7	
Codex	10	86.9	92.9	36.7	59.5	77.2	86.9	75.1	85.3	
Codex	20	86.3	94.5	50.6	65.8	75.7	88.6	75.6	87.5	
Codex	40	92.9	95.1	57.0	78.5	83.0	93.2	82.6	92.0	
Codex	60	92.3	95.1	67.1	77.2	84.5	95.1	84.6	93.0	

Table 4: Comparison of Codex with random prompt construction and DocTer: Precision, Recall, and F1 Score (%) for Extracting Specifications from DL Documentation

Approach	K	TensorFlow	PyTorch	MXNet	Overall
DocTer	898	89.4/72.5/80.1	78.0/78.3/78.2	87.8/71.2/78.6	86.8/72.8/79.1
Codex	10	75.0/72.0/73.5	73.3/68.8/71.0	74.8/64.4/69.2	74.6/67.8/71.0
Codex	20	79.7/72.0/75.6	75.5/78.8/77.2	76.1/67.0/71.3	77.3/70.6/73.7
Codex	40	80.9/82.3/81.6	77.4/78.7/78.0	80.5/73.6/76.9	80.9/81.3/78.7
Codex	60	83.8/82.5/83.2	77.8/80.6/ <b>79.2</b>	79.8/80.7/ <b>80.3</b>	80.5/81.3/ <b>81.1</b>

as no significant performance differences were observed among different categories.

As discussed in Section 3.2, we treat data from Jdoctor-data of different tag types and data from DocTer-data of different libraries as separate datasets. We report the accuracy and F1 metrics for them separately, as well as the overall accuracy/F1.

#### 5 EVALUATION RESULTS

## 5.1 RQ1: Specification Extracting Capabilities

We evaluate LLMs on both Jdoctor-data and DocTer-data using random retrieval strategy for prompt construction (Section 3.2.1). We select Codex as the subject model (Section 3.4). Results are presented in Table 3 and Table 4. We reproduce the baseline methods (Jdoctor and DocTer) on the evaluation set (Section 3.1), and report the accuracy for Jdoctor in row *Jdoctor* of Table 3, and precision/recall/F1 for DocTer in row *DocTer* of Table 4. Our results are consistent with the numbers reported in the original papers (within 1.3-2.5% margins).

As described in Section 3.2, we manually post-process the specification generated for Jdoctor-data and present the raw accuracy (automatically calculated by the script) in col. "Raw" and the final accuracy (after manual correction) in col. "Processed" in Table 3. For Jdoctor (row Jdoctor), these two values are the same. The manual evaluation required an average of 14.3 minutes per experiment.

The columns K in Table 3 and Table 4 represent the number of examples in the prompts (Section 3.2). Since Jdoctor relies on manually defined heuristics, we leave the corresponding cell blank ("-") in Table 3. For DocTer, we list the average number of annotated examples used for rule construction (2,696 / 3 = 898) as K.

Results for Jdoctor-data As shown in Table 3, Codex achieves an overall accuracy of 85.3% using only 10 randomly chosen examples from each comment type (i.e., 30 in total) and outperforms Jdoctor, which has an accuracy of 81.7%. Codex outperforms Jdoctor in terms of accuracy for @return and @throws comments, using just 20 and 10 randomly selected examples, respectively, and achieves comparable performance to Jdoctor for @param comments.

Table 5: Comparison of Codex using SR prompt construction and Jdoctor: Accuracy (%) for Extracting Pre- and Postconditions from Javadoc Comments.

Approach K	v	(	param	@return		@throws		Overall	
Арргоасп	K	Raw	Processed	Raw	Processed	Raw	Processed	Raw	Processed
Jdoctor	-	96.7	96.7	63.9	63.9	78.5	78.5	81.7	81.7
Codex + SR	10	90.2	98.9	68.4	82.3	85.7	92.2	84.9	92.9
Codex + SR	20	94.5	98.9	69.6	82.3	87.6	93.2	87.4	93.5
Codex + SR	40	95.1	99.5	64.6	79.7	89.8	95.1	88.3	94.5
Codex + SR	60	97.3	99.5	69.6	81.0	91.7	96.4	90.6	95.4

Table 6: Comparison of Codex using SR Prompt Construction and DocTer: Precision, Recall, and F1 Score (%) for Extracting Specifications from DL Documentation.

Approach	K	TensorFlow	PyTorch	MXNet	Overall
DocTer	898	89.4/72.5/80.1	78.0/78.3/78.2	87.8/71.2/78.6	86.8/72.8/79.1
Codex + SR	10	86.3/83.6/ <b>84.9</b>	84.7/83.4/ <b>84.0</b>	88.0/87.0/ <b>87.5</b>	86.9/85.2/86.0
Codex + SR	20	87.3/86.0/86.6	85.4/84.6/85.0	88.7/88.7/88.7	87.7/87.1/87.4
Codex + SR	40	87.1/86.8/87.0	84.6/85.0/84.8	88.7/89.4/89.0	87.5/87.8/87.6
Codex + SR	60	88.0/87.2/87.6	86.2/86.2/86.2	88.8/89.7/89.2	88.1/88.3/88.2

**Results for DocTer-data** As shown in Table 4, with only 60 random examples from each library (180 in total), Codex achieves an overall F1 score of 81.1%, outperforming DocTer, which has an F1 score of 79.1% and requires 2,696 annotated examples. Furthermore, Codex surpasses DocTer for TensorFlow, PyTorch, and MXNet in terms of F1 score using only 40, 60, and 60 examples, respectively.

**Finding 1:** Codex, with a small number (10–60) of randomly selected examples, outperforms state-of-the-art specification extraction techniques, Jdoctor and DocTer, by 2.0–11.3%.

# 5.2 RQ2: Prompt Construction Strategies

Table 5 and Table 6 reveal that Codex, when employing the SR strategy, outperforms both Jdoctor and DocTer, even with only 10 examples selected in the prompt from each type/category.

Fig. 6 showcases the effectiveness of random and SR strategies across prompt sizes. SR strategy consistently outperforms both the random strategy and traditional specification techniques across different prompt sizes, highlighting the importance of an appropriate prompt construction strategy for improved FSL performance.

**Finding 2:** The semantic retrieval strategy further improves Codex's performance, leading to a 11.2–13.7% improvement over Jdoctor and a 6.9–9.1% increase over DocTer.

#### 6 RQ3: PROS AND CONS: FAILURE DIAGNOSIS

We manually examine failing cases of both LLM-based methods and baseline approaches (i.e., Jdoctor and DocTer) to study failure symptoms and root causes in a comparative manner, aiming to provide insights and directions for future techniques.

Fig. 7 presents the comparative performance of the LLM method based on Codex and the baseline methods as Venn diagrams. Fig. 7a presents the number of unique specifications that are correctly extracted/generated by the Codex (C) method and Jdoctor (J), along with the numbers that both methods succeed and fail. Similarly, Fig. 7b presents the comparative performance of Codex (C) and DocTer (D) on DocTer-data. Symbol "+" indicates correct, while "-" denotes incorrect results. For example, "C+" indicates the correct

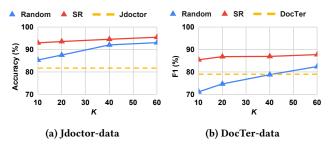


Figure 6: Comparison of FSL performance using Random and Semantic Retrieval (SR) for prompt sizes (K) from 10 to 60.

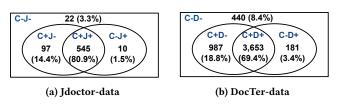


Figure 7: Venn diagrams of specification generation in the two datasets. C: Codex; J: Jdoctor; D: DocTer. "+" indicates correct, while "-" denotes incorrect results. The numbers are from experiment using Codex with SR and K=60.

cases by Codex and "J+" denotes the correct cases by Jdoctor, and the section "C+ J+" indicates cases where both methods succeed.

Fig. 7a shows that both the LLM method and Jdoctor perform well on majority of the cases (80.9%), indicating that the LLM quickly learns most specification extraction rules from a small number of examples in the prompts. The LLM method has more (12.9%) unique correct cases than Jdoctor, which indicates the generalizability of LLMs from extensive pretraining. There are a few cases that both methods fail. This could be due to the inherent difficulties such as incomplete software text.

To better understand the pros and cons of different methods, we investigate the symptoms and the underlying causes of the failing cases. We sample 15 cases from each section of the Venn diagrams with at least one of the methods giving wrong results. As the "C-J+" section has only 10 cases, we include all of them in our analysis. The sampling results in 85 failing cases of Codex and 90 failing cases of the baseline methods. Two authors conduct the symptom and root cause categorization, with a third author resolving any disagreements.

## 6.1 Failure Symptom Analysis

We classify failure symptoms into four distinct categories and analyze the distributions of these categories. The bars in Fig. 8 illustrate the distributions of failure symptoms for various methods, with color coded for each symptom. Each bar shows the distributions of the symptoms from different sections of the Venn diagrams in Fig. 7 for Codex, Jdoctor, and DocTer. For example, bar "Codex(C-J+)" in Fig. 8a denotes the distributions of Codex's failure symptoms on Jdoctor-data within the "C-J+" section (Codex fails, and Jdoctor succeeds). "C-" indicates the cases where Codex fails regardless of Jdoctor's results, subsuming "C-J+" and "C-J-". When both fail as in "C-J-", "Codex(C-J-)" shows the failure symptoms categories for Codex output and "Jdoctor(C-J-") for Jdoctor output.

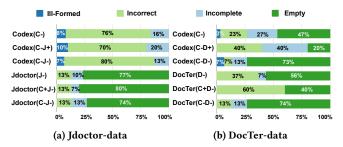


Figure 8: Distributions of symptoms in failing cases across approaches and datasets. The y-axis is "approach (section)".

Category "ill-formed" refers to invalidly formed generated specifications. For Jdoctor-data, this denotes syntactical errors or grammatical mistakes, while for DocTer-data, it refers to improper specifications forms. For example, a boolean is generated instead of the expected numerical range. "Incorrect" indicates specification errors, while "Incomplete" denotes the specification is a strict subset of the ground truth. For DocTer-data, if the ground-truth specification for the dtype category includes both int32 and int64, generating only int32 is incomplete, whereas generating bool is incorrect. "Empty" denotes a missing specification. For DocTer-data, each specification contains four categories (Section 3.1). If the specification for one of the categories is empty while the ground truth is not, it is considered an empty type of failure.

- (1) Existing specification-extraction techniques are much more likely to generate no specifications than LLMs. For both datasets, the most common failure symptom among baseline methods (Jdoctor and DocTer) is "Empty" (77% and 56%), indicating that the methods fail to generate any specifications. For Codex, none of the failing cases for Jdoctor-data are empty, while only 47% of the failing cases for DocTer-data are empty.
- (2) LLMs are more likely to generate ill-formed and incomplete specifications. A small fraction (8% and 3%) of Codex's failing cases are ill-formed, while traditional methods do not exhibit this issue. This is because traditional methods are rule-based and therefore guarantee the validity of the generated specifications, whereas LLMs are generative models and do not ensure the correctness of their output. Fig. 8 also shows that LLMs are more likely to generate incomplete specifications. For instance, when given the description "tuple/list of 1 int", Codex only generates tuple for the *structure* type of spec. and fails to include list. Such an error is unlikely to occur in rule-based methods, as they match the entire sequence of data types and extract them directly from the document as specifications while LLMs use sampling to decode outputs from a distribution, which may occasionally miss tokens.

**Finding 3:** Compared to LLMs, existing specification-extraction approaches are much more likely to generate no specifications (e.g., 77% versus 0%), while LLMs are more likely to generate ill-formed or incomplete specifications.

**(3) Comparative Symptom Analysis** We conduct further analysis on the distributions of failure symptoms in various sections of

the Venn diagrams (Fig. 7), and present our results in Fig. 8. The results show that for Jdoctor-data (Fig. 8a), the symptom distributions of Codex and Jdoctor are consistent across different sections.

From bars "Codex(C-J+)" and "Codex(C-D+)", compared to baselines, if Codex fails (and the baselines succeed), it tends to produce incorrect or incomplete answers. In contrast, from bars "Jdoctor(C+J-)" and "Jdoctor(C+D-)", when the baselines fail (and Codex succeeds), they tend to produce empty answers. The reason is that the Jdoctordata examples provided to the LLMs are never empty and hence the LLMs always generate some results for the test queries for Jdoctordata. In contrast, some of the specification categories (e.g., dtype) of DocTer-data examples (provided to the LLMs) may be empty. The LLMs learn that empty is a possible result for the DocTer-data dataset. This is due to the nature of the methods. The baselines are based on rules. When rules are inapplicable, they tend to produce empty results. In contrast, LLMs produce results by predicting missing tokens. They may produce empty results when empty is a legitimate token. The results are in line with the precision and recall in Table 6, that Codex has a much higher recall than DocTer (e.g., 88.3% versus 72.8%) with a comparable or slightly better precision (e.g., 88.1% versus 86.8%).

Moreover, in DocTer's unique failures (i.e., bar "DocTer(C+D-)"), we observe a relatively large number of incorrect cases, partially due to the incorrect rules, which will be discussed in Section 6.2.2.

We noticed that "incomplete" failing cases of Codex are more dominant in "Codex(C-D+)" (40%) than in "Codex(C-D-)" (13%), indicating that DocTer correctly handles most of these cases. Conversely, all of the "incomplete" failing cases of DocTer are challenging cases (falling into "C-D-"). This observation aligns with our earlier **observation (2)** that LLMs are more likely to yield incomplete results due to their design nature, while DocTer tends to produce incomplete results only when the cases are particularly difficult, and is more inclined to generate empty results.

# 6.2 Failure Root Cause Analysis

In this section, we first categorize the root causes of failures and then study their distributions. At the end, we perform a comparative study based on the sections in the Venn diagrams in Fig. 7.

- 6.2.1 LLM Failure Root Causes. We first present the root cause categories and distributions by LLMs. Since LLM results are difficult to interpret, it is in general difficult to determine the root causes of failing cases by LLMs. We hence determine the root cause by finding a fix for it. The nature of the fix indicates the root cause. In some cases, the failure may be fixed in multiple ways. We consider the one requiring the least effort the root cause. Fig. 11 presents the distributions of the root causes of Codex in different sections of the Venn diagrams (Fig. 7).
- (1) Ineffective Prompts means that the failure is due to the ineffectiveness of the examples in prompt, even with SR. Although SR significantly improves FSL's performance (Section 5.2), it occasionally falls short in selecting the appropriate examples. If we can fix a failing case by manually selecting more relevant example(s) to the prompt, or simply altering the order of the examples in the original prompt, we consider the failure is due to ineffective prompts.

According to bars "Codex(C-)" from Fig. 11a (Jdoctor-data) and Fig. 11b (DocTer-data), 32% and 37% Codex's failures on the two

```
Signature: tf.sparse.fill_empty_rows(sp_input,...)
Description: sp_input-A'sparse?ensor' with shape '[N, M]'.
Constraints:
shape: [N, M]
ndim: Null

Signature: tf.math.lbeta(x,...)
Description: x - A rank 'n + 1' Tensor', 'n >= 0' with type 'float', or 'double'.
Constraints:
shape: Null
ndim: >=1

Signature: tf.sparse.softmax(sp_input,...)
Description: sp_input-N'-D' SparseTensor', where 'N' >= 2'.
Constraints:
shape: Null
ndim: >=2

Completion
Null
Null
New completion
```

Figure 9: Example of the "Ineffective Prompt" root cause. Yellow, blue, and green highlight the original prompt (simplified), the generated completion, and an added example that helps the LLM generate the correct specification (in green).

```
+ Relevant functions:

+ Unit(net.sf.freecol.common.model.Game game) Additional domain knowledge

+ ... kearchForDanger(int range,float threat) knowledge

+ ... (K examples)

Signature: isInDanger(int range,float threat) Javadoc comment: @return True if a threat was found.

- Condition: this.getTile().isInDanger(range,threat) -- methodResultID==true

+ Condition: this.searchForDanger(range,threat) -- methodResultID==true
```

Figure 10: Example of the "Missing Domain Knowledge" root cause. Yellow, blue, and green highlight the original prompt (simplified), the originally generated completion, and additional domain knowledge, as well as the new completion.

datasets are due to this reason. We find that the order of examples plays a crucial role, as 21% of the failure cases in this category are resolved by rearranging the order of the examples.

Fig. 9 presents a portion of the prompt related to the target parameter <code>sp\_input</code> for API <code>tf.sparse.softmax</code>. Codex fails to generate the specification <code>ndim:>=2</code>, which is not explicitly stated in the description and requires Codex to comprehend the implicit relationship between N and its value range, i.e., "N>=2". We add the example that contains such implicit constraints, enabling Codex to generate the correct specification.

- (2) Missing Domain Knowledge refers to LLM failures due to insufficient domain knowledge. For instance, in Fig. 10, Codex generates a specification using a non-existent function, isInDanger, instead of searchForDanger. This issue arises as Codex lacks relevant context, such as the methods in the class, while Jdoctor employs a search-based approach examining all methods in the relevant classes. This result uncovers LLMs' limitation compared to traditional search-based methods: a deficiency in domain knowledge. To validate our hypothesis, we manually incorporate relevant domain knowledge into the prompt, alongside the provided examples. For instance, we list all methods within the class prompt's beginning, as shown in Fig. 10. With this domain knowledge, Codex successfully generates the accurate specification, utilizing the correct function (in green). Fig. 11 shows that 28% and 20% of Codex's failures are due to missing domain knowledge.
- (3) Wrong Focus denotes instances where LLMs fail to focus on crucial keywords or are misguided or diverted by other content. For example, Fig. 13 shows an LLM failing to generate the correct spec. from the original document (in yellow), numeric, which specifies

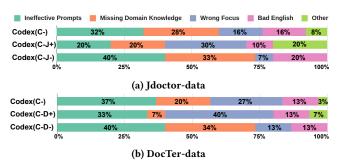


Figure 11: Distributions of root causes of Codex's failures

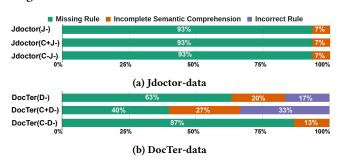


Figure 12: Distributions of root causes for baselines' failures

values: 1-D or higher numeric `Tensor`.
values: 1-D or higher `numeric` `Tensor`.

Figure 13: Example of the "Wrong Focus" root cause. A minor adjustment (quoting the keyword) enables the LLM to accurately generate specifications.

the data type of the input tensor. By employing a slightly revised description that merely quotes the keyword (in blue), Codex successfully generates numeric for *dtype*. Fig. 11 reveals that 16% and 27% of Codex's failures are due to the wrong focus for the two respective datasets.

Such modifications do not affect rule-based methods like Doc-Ter, which rely on syntactic structure and remain unaffected by quotation marks. To identify failures caused by wrong focus, we apply three input mutation strategies: *minor modifications* by simply adding quotation marks to the keywords; *rewriting the sentence* while preserving the same syntactic structure (e.g., changing "A or B" to "B or A"); and *deleting redundant content* to help the LLM concentrate on the essential parts. All three strategies involve simple and semantics-preserving mutations. We found that 42% of such cases can be resolved by merely quoting the keyword(s).

- (4) Bad English refers to instances where the original documents or comments are poorly written, ambiguous, or hard to understand even for humans. Rewriting the sentence to clarify its meaning enables LLMs to generate correct specifications. According to Fig. 11, 16% and 13% of Codex's failures are due to bad English.
- (5) Other we group the non-prevalent categories as "other", including "contradictory document" and "unclear". The former refers to buggy or self-contradictory original comments or documents, causing discrepancies between dataset annotations and LLM-generated specifications. We identified two human mistakes and reported them to the developers. "Unclear" indicates failures with unclear

root causes, which we fail to fix despite various attempts. Fig. 11 shows that 8% and 3% of Codex's failures are in these categories.

**Finding 4:** The two dominant root causes combined (ineffective prompts and missing domain knowledge) result in 57–60% of Codex failures on the two datasets.

The results suggest that incorporating domain knowledge, such as program context, and selecting better examples with optimal order, could enhance LLMs' effectiveness in specification generation.

- 6.2.2 Jdoctor and DocTer Failure Root Causes. We manually investigated the 90 failing cases for Jdoctor and DocTer and identified three root causes: missing rule, incomplete semantic comprehension, and incorrect rule. The distributions are in Fig. 12.
- (1) Missing Rule refers to the absence of relevant rules or patterns, usually resulting in "empty" specifications (Section 6.1). A notable 93% and 63% of the baseline failing cases of Jdoctor and DocTer respectively fall into this category, exposing a limitation of rule-based methods that are heavily dependent on manually defined or limited rules.
- **(2) Incomplete Semantic Comprehension** describes instances where rule-based methods successfully match a part of the sentence but fail to grasp the semantics of the entire sentence. This lack of comprehensive understanding leads to incorrect results. For instance, DocTer extracts a *structure* specification vector from the description "Initializer for the bias vector" but does not consider the full context or relationships among elements, ultimately impacting the correctness of the extracted specifications. In Fig. 12, 7% and 20% of the failing cases in the two datasets are due to this reason.
- (3) Incorrect Rules denote the applied rules are incorrect. For example, DocTer extracts boolean as the *dtype* spec. from the description of a parameter operands: "the operands to compute the Einstein sum of..." as DocTer's rule maps the sentence pattern "to compute" to boolean. This is because DocTer automatically constructs the rules (from syntactic patterns to specifications) based on their co-occurrence in the annotated dataset. Such an approach can potentially introduce incorrect rules, leading to incorrect extractions. In Fig. 12, 17% of DocTer's failing cases are due to *incorrect rules*, while Jdoctor does not have any of such failures since their rules are all manually defined.
- *6.2.3 Comparative Root Cause Analysis.* We study the root cause distributions of Codex, as shown in Fig. 11, and compare them with those of the baseline methods (Fig. 12).

Bars "Codex(C-J+)" and "Codex(C-D+)" show that in cases where the baseline methods succeed, Codex's dominating failure causes are ineffective prompts and wrong focus. Notably, the wrong focus is particularly prevalent here, in contrast to sections "C-J-" and "C-D-" where both approaches fail. It suggests that wrong focus presents a unique challenge for the LLMs. The results suggest that combining LLMs and baselines could generate more accurate specifications since they have complementary capabilities. To enhance LLMs for a hybrid approach, addressing wrong focus and ineffective prompts is crucial, e.g., by rewriting the document sentences and adding better examples to prompts (including optimal example orders).

From bars "Codex(C+J-)" and "Codex(C+D-)" where Codex succeeds and the baseline methods fail, we observe that the unique baseline failures are primarily due to missing rules and incomplete semantic comprehension. In other words, when prompts and software texts are of high quality, LLMs demonstrate outstanding generalizability, unbounded by rule sets. They make predictions based on entire descriptions rather than just parts of them. Notably, 17% of DocTer's unique failures are due to incorrect rules, all of which can be addressed by Codex as suggested in the figure. We suspect that any automatic rule inference techniques may suffer from such problems if human corrections are not in place.

**Finding 5:** Compared to rule-based methods, Codex suffers from ineffective prompts and wrong focuses, which are inherent to LLMs and cause 50-73% *unique* Codex failures. In contrast, rules are often insufficient or incorrect for existing approaches, causing 73–93% *unique* baseline failures, as rules are extracted manually or semi-automatically from a limited dataset.

## 7 RQ4: MODEL COMPARISON

Table 7 and Table 8 present the performance, cost, and response time of 11 LLMs in comparison to baselines. The non-free models charge based on the number of tokens processed; hence, the cost varies with the value of K. We report the total cost for all requests when K=10. Symbol "-" denotes experiments that we cannot conduct due to token limitations, as discussed in Section 4.1 More experiments on DocTer-data are skipped since prompts for DocTer-data are much longer than those for Jdoctor-data, making them inapplicable for certain settings (Section 4.1). For instance, with K=40, the median prompt length for DocTer-data is 5,024, exceeding GPT-3.5's token limit of 4,096 (Table 2), while the median length for Jdoctor-data is 2,492.

Overall, generic LLMs with as few as 10 domain examples achieve better or comparable performance as custom-built state-of-the-art specification extraction techniques such as DocTer. Specifically, seven out of the 11 models outperform Jdoctor's 81.7% accuracy. For DocTer-data, four out of the 11 models outperform DocTer's 79.1% F1 score and all remaining seven models' F1 scores are only short of a few percentage points from DocTer's.

Table 7 and Table 8 also show that the response time for specification extraction is quick for practical uses. The only exception is BLOOM, which has a similar size as GPT-3 though, is run with fewer computing resources and on slower machines [3].

**Finding 6:** Most LLMs, with quick response time, achieve better or comparable performance as custom-built existing specification-extraction techniques.

**Codex.** Among all 11 models, Codex achieves the best performance on DocTer-data, achieving an overall F1 score of 88.2% (Table 8). In addition, it achieves one of the highest overall accuracies of 95.4% on Jdoctor-data (Table 7). Compared to the Codex model, which is free with much fewer parameters (Table 2), paid counterparts GPT-3.5 and GPT-3 add no F1 gains on DocTer-data. Specifically, GPT-3's total cost of \$78.6 (\$12.6 when K=10) on DocTer-data causes a 1.7% F1 score degradation. GPT3's tiny accuracy improvement of 0.2% comes at an additional cost of a total of \$163.8 on Jdoctor-data. The

Table 7: Comparison of Different Models with SR on Jdoctordata: Overall Accuracy, Time, and Cost.

Appro	ach/	Ove	rall Ac	curacy	(%)	Avg. time (s)	Cost
Model (+SR)		K=10	20	40	60	per request	K=10 (\$)
Jdoctor			81	.7		-	0
Codex	davinci	92.9	93.5	94.5	95.4	1.7	0
GPT-3	davinci	92.9	93.5	94.4	95.6	1.2	12.6
GP 1-3	curie	54.3	66.4	-	-	0.5	1.26
GPT-3.5	turbo	89.3	87.9	87.4	84.4	0.6	1.26
BLOOM		86.8	-	-	-	6.2	0
	16B	86.4	88.4	-	-	3.9	0
CodeGen	6B	86.0	88.4	-	-	2.0	0
(Multi)	2B	82.8	87.4	-	-	1.2	0
	350M	68.7	78.5	-	-	0.4	0
Incoder	6B	52.7	61.6	-	-	1.4	0
mcoder	1B	54.2	62.9	-	-	0.4	0

exceptional performance of Codex may attribute to its specialized training for generating code from natural language descriptions. Software specifications are typically written in a formal structure, making Codex a suitable and cost-effective tool for this task. As Table 2 shows, Codex supports a larger number of input tokens (8,000) than other models, which enables us to add more examples to prompts for better performance.

**Finding 7:** Codex is the most competitive model for extracting specifications, with among the highest performance of 88.2% and 95.4%, \$0 cost, long prompt support, and quick responses.

Paid Models (GPT-3 Davinci, GPT-3 Curie, and GPT-3.5) GPT-3 Davinci (175B parameters, \$0.02 per 1,000 tokens) achieves comparable or slightly worse performance than Codex given the same number of examples. However, GPT-3 Davinci supports fewer prompt tokens, preventing it from achieving higher performance with more examples on DocTer-data. In addition, it is much more costly and bigger than Codex. As OpenAI's claimed second best yet cheaper model (\$0.002 per 1,000 tokens), Curie's performance on specification extraction is relatively poor. Despite being more recent, GPT-3.5 Turbo has lower performance on both Jdoctor (11.2% accuracy decrease) and DocTer (2.8% F1 decrease) compared to GPT-3 Davinci, possibly due to its optimization for conversations.

Open-Source Models (BLOOM, CodeGen, and InCoder) An open-source GPT-3 alternative, BLOOM underperforms, with 6.1% and 6.5% lower performance than GPT-3 Davinci on Jdoctor-data and DocTer-data respectively. A non-GPT-3 model, CodeGen achieves comparable results as BLOOM. We conducted the experiment for DocTer-data with CodeGen's Mono series, specifically trained for Python (Section 3.3), and they underperform its Multi series by 0.8% to 4.9%, potentially due to less generalizability. InCoder significantly underperforms CodeGen on Jdoctor-data, likely due to its pre-training data containing more Python (50 GB) than Java code (6 GB).

**Finding 8:** Codex's strong performance makes GPT-3 Davinci less desirable given its size and cost. Economical alternatives GPT-3 Curie and GPT-3.5 have lower performance. CodeGen and BLOOM are reasonable open-source alternatives.

Table 8: Comparison of Different Models with SR on DocTerdata: Overall F1 Score, Time, and Cost.

Appro	Approach/		Overall	F1 (%)		Avg. time (s)	Cost
Model (+SR)		K=10	20	40	60	per request	K=10 (\$)
DocTer			79.1			-	0
Codex	davinci	86.0	87.4	87.6	88.2	2.2	0
GPT-3	davinci	84.6	86.5	-	-	2.1	26.2
Gr 1-3	curie	76.9	-	-	-	0.7	2.62
GPT-3.5	turbo	81.3	83.7	-	-	0.8	2.62
BLOOM		78.1	-	-	-	12.6	0
	16B	80.4	-	-	-	7.5	0
CodeGen	6B	78.5	-	-	-	3.9	0
(Multi)	2B	75.1	-	-	-	3.3	0
	350M	74.6	-	-	-	1.1	0
Incoder	6B	76.4	-	-	-	2.1	0
meoder	1B	78.7	-	-	-	0.6	0

## 8 THREATS TO VALIDITY

**Reproducibility** Many evaluated models, including the now-retired Codex (as of March 23rd, 2023), are not open-sourced, posing a threat to reproducibility. Nonetheless, our conclusion that LLMs with FSL outperform existing approaches remains valid. The open-sourced CodeGen, while not the best, still surpasses the baseline methods, Jdoctor and DocTer (Section 7). We expect that future models will continue to improve upon these results.

**Manual Evaluation** To address the equivalence specification issue in Jdoctor-data (Section 3.2), we manually evaluated results for RQ1, RQ2, and RQ4 (Sections 5.1, 5.2, 7), and analyzed 175 samples in RQ3 (Section 6). To minimize biases, two authors independently conducted evaluations, resolving disagreements with a third author.

#### 9 RELATED WORK

to the studied datasets.

Software Specifications Datasets and Extraction Methods Existing techniques for extracting software specifications from text, such as rule-based [8, 20, 51, 52, 56, 60] or ML-based methods [8, 32, 51], require manual effort and domain knowledge, and lack generalizability across domains. We use FSL with LLMs that require little annotated data and offer improved generalizability. Techniques like @tcomment [52], Toradocu [20], and C2S [59] also extract specifications from Javadoc. They are excluded from this study as C2S is unavailable and the others are outdated or less effective [8, 59] than Jdoctor. Advance [32] and DRONE [60] are excluded from this study due to the absence of ground-truth specifications and their domain-specific nature, making them inapplicable

**Few-shots Learning** FSL adapts pre-trained LLMs to specific tasks with limited labeled data, yielding performance improvements across various tasks [11, 15, 24, 45, 47, 54]. Applied to software engineering tasks, FSL demonstrates competitive or superior results compared to state-of-the-art techniques [13, 23, 26, 35]. We are the first to explore LLMs with FSL for software specification generation.

Other LLMs and Tasks Other LLMs have been developed, yet we do not study them as they are unsuitable for our task [17], less effective [7, 53, 58], unable to fit in our devices [6], or unavailable [39]. Besides specification generation, LLMs have been used for other natural language generating tasks [7, 11, 31, 44, 53] and software

engineering tasks such as code completion [5, 16, 18, 36]. Our work is the first to study 11 LLMs for specification generation.

#### 10 CONCLUSION

We conduct the first study that examines the effectiveness of 11 LLMs for specification generation. Our findings include that most LLMs achieve better or comparable performance, with quick response times, compared to traditional techniques. The best-performing model, Codex, outperforms existing approaches by 9.1–13.7% with semantically similar examples, while CodeGen and BLOOM are good open-source alternatives. The two dominant root causes combined (ineffective prompts and missing domain knowledge) result in 57–60% of LLM failures. Our study offers insights for future research to improve specification generation including providing better examples in the LLM prompt and adding domain knowledge.

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