

Beyond LLMs: An Exploration of Small Open-source Language Models in Logging Statement Generation

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Effective software maintenance heavily relies on high-quality logging statements, but manual logging is challenging, error-prone, and insufficiently standardized, often leading to inconsistent log quality. While large language models have shown promise in automatic logging, they introduce concerns regarding privacy, resource intensity, and adaptability to specific enterprise needs. To tackle these limitations, this paper empirically investigates whether Small Open-source Language Models (SOLMs) could become a viable alternative via proper exploitation. Specifically, we conduct a large-scale empirical study on four prominent SOLMs, systematically evaluating the impacts of various interaction strategies, parameter-efficient fine-tuning techniques, model sizes, and model types in automatic logging. Our key findings reveal that Retrieval-Augmented Generation significantly enhances performance, and LoRA is a highly effective PEFT technique. While larger SOLMs tend to perform better, this involves a trade-off with computational resources, and instruct-tuned SOLMs generally surpass their base counterparts. Notably, fine-tuned SOLMs, particularly Qwen2.5-coder-14B, outperformed existing specialized tools and LLM baselines in accurately predicting logging locations and generating high-quality statements, a conclusion supported by traditional evaluation metrics and LLM-as-a-judge evaluations. Furthermore, SOLMs also demonstrated robust generalization across diverse, unseen code repositories.

CCS Concepts: • Software and its engineering → Maintaining Software.

Additional Key Words and Phrases: Logging Statement, Logging Practice, Large Language Model

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1 Introduction

Logs are textual records generated during software execution to capture runtime events, states, and contextual information [73]. A typical log statement consists of three components: a verbosity level, logging variables, and logging texts [16]. In particular, as demonstrated in the example below, the logging level (such as *debug*) reflects the event's severity; the logging variables (like *terminalState*) hold critical run-time data about system states; meanwhile, the logging text (for instance, *Stopping the checkpoint services with state { }.*) offers a static explanation of the system's actions. High-quality logs provide actionable insights for developers to diagnose failures, optimize system behavior, and ensure operational reliability. However, the absence or inadequacy of logging statements can severely hinder downstream tasks such as anomaly detection and failure diagnosis, leading to prolonged debugging cycles and increased maintenance costs. Consequently, the strategic placement and content design of log statements directly influence the effectiveness of software maintenance and evolution [60].

```
LOG.debug("Stopping the checkpoint services with state { }.", terminalState);
```

Manual logging poses significant challenges for developers, making it a complex and error-prone task. First, the absence of universal logging guidelines results in inconsistent practices across development teams, where decisions about log placement, content, and verbosity heavily rely on individual developers' expertise and intuition. This lack of standardization often leads to logs that vary widely in quality, granularity, and utility [3]. Second, striking a balance between log quantity and quality is inherently difficult: excessive logging generates vast amounts of data, increasing storage costs, slowing down system performance, and overwhelming analysis tools with irrelevant information, while insufficient logging risks omitting critical runtime details necessary for diagnosing failures or understanding system behavior [71]. Moreover, manual logging is time-intensive, requiring developers to anticipate potential failure points and system states during code writing, which is challenging in large, complex, or rapidly evolving software systems. The cognitive burden of determining optimal logging points and crafting meaningful log messages further exacerbates the problem, often leading to logs that are either too vague to be actionable or overly detailed, obscuring key insights [15]. Additionally, as software evolves, manually inserted logs may become outdated or misaligned with new system behaviors, requiring continuous maintenance to remain relevant. These challenges highlight the need for automated, systematic approaches to logging [81].

To address these challenges, at the early stage, researchers have explored automated logging techniques by decomposing the problem into sub-tasks, such as where-to-log (identifying code locations for logging) [37, 79], what-to-log (generating static content) [8, 45], and log-level suggestion [18, 38, 42]. However, these fragmented approaches lack integration into a unified, end-to-end framework for generating complete logging statements. Recent advances in pre-trained language models (LMs) have opened new avenues for automated logging. LANCE [48] and LEONID [47] pioneered the use of sequence-to-sequence models (e.g., T5 [53]) to generate logging statements directly from code contexts. Subsequent tools, such as, Fastlog [67], Unilog [68], and SCLogger [36], further leveraged large language model (LLM) to improve logging quality. Notably, Unilog and SCLogger adopted prompt-based methods with LLMs like GPT-3.5 and Codex, achieving state-of-the-art performance by harnessing LLMs' code comprehension and natural language generation capabilities.

Despite their effectiveness, LLM-based logging tools face the following three limitations. First, privacy concerns arise when proprietary code is processed via commercial LLM APIs (e.g., OpenAI), risking exposure of sensitive intellectual property [72]. For instance, Samsung banned employee use of ChatGPT and other generative AI tools after an engineer accidentally leaked sensitive source code

to ChatGPT [27]. Second, the resource intensity of LLMs—requiring thousands of GPU hours for training and generating substantial carbon emissions—contradicts sustainable computing goals [21]. Researchers have shown that making requests to LLMs can lead to annual carbon emissions greater than the emission during training such LLMs [6]. Additionally, LLMs often struggle to adapt to enterprise-specific logging styles due to varying organizational needs [14, 17, 55]. Enterprises may require unique verbosity levels, from concise logs for performance to detailed ones for debugging, which LLMs may not consistently deliver. Error prioritization also differs, with some organizations focusing on critical alerts and others on detailed behavioral logs, challenging LLMs' generic outputs. Compliance-driven requirements, such as general data protection regulation [9], demand specific log formats or data anonymization that LLMs may not inherently support. This misalignment often necessitates manual refinement of LLM-generated logs to meet enterprise standards.

Recently, Small open-source language model (SOLM) has demonstrated competitive performance in many software engineering tasks [21, 46], such as program repair [59] and comment rectification [56]. Thus, SOLMs, which defined as open-source models smaller than 14B parameters, offer a promising alternative to LLMs because it can theoretically address the above three limitations in logging automation. By enabling local deployment on a single consumer-grade graphics card (e.g., A100) [70], SOLMs mitigate the privacy risks associated with processing proprietary code through commercial LLM APIs. Additionally, their reduced computational requirements lower resource costs and carbon emissions, aligning with sustainable computing goals. Furthermore, SOLMs can be fine-tuned on enterprise codebases to adapt to unique logging styles, addressing the challenge of aligning logs with organizational practices. However, despite their theoretical ability, no empirical studies have systematically evaluated SOLMs' feasibility for this task.

In this paper, we conduct an empirical study on four prominent SOLMs, namely LLaMA, Mistral, CodeLLaMA, and Qwen2.5coder, to explore the potential utility of SOLMs in the automatic generation of logging statements. For a thorough evaluation of the effectiveness of SOLMs, we pose the following four research questions:

RQ1: What are the most effective interaction strategies for using SOLMs in logging generation? Diverse prompting techniques can influence the performance of SOLMs without the need for retraining. Gaining insight into their effects can help improve the generation of logging statements across different contexts.

Result. Retrieval-augmented generation outperforms in-context learning and chain-of-thought, significantly enhancing the performance of logging automation task.

RQ2: What's the best strategy using SOLMs for automated logging statement generation? Many strategies such as parameter-efficient fine-tuning (PEFT) techniques, model size, and model type may influence the efficacy. Thus, we further investigate the extent of their impact, which may offer insights into the optimal selection of strategies for enhancing SOLM performance.

Result. LoRA demonstrate the most consistent and superior results when fine-tuning with PEFT techniques. For models with more than 3B parameters, performance in generating logging statement improves with more parameters, but increases computational costs, indicating a performance-resource trade-off. The instruct variant of SOLM model outperforms its base counterpart, benefiting from its instruction-tuned foundation.

RQ3: How effectively do SOLMs compare to existing methods and LLM baselines in automated logging statement generation? After establishing the optimal strategies for employing SOLMs, we aims to investigate the performance of SOLMs in automated logging compared to existing method and the prominent LLMs.

Result. Fine-tuned SOLM, particularly Qwen2.5-coder-14B, outperform both existing methods and LLMs across all evaluated metrics, demonstrating superior logging location accuracy and

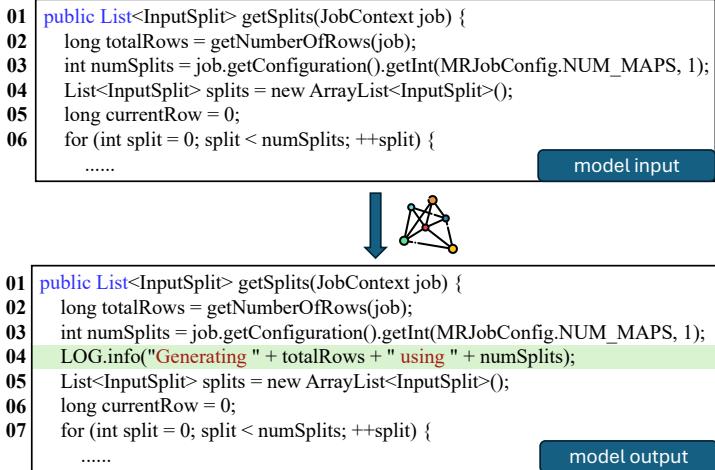


Fig. 1. Task formulation: given a method which missing a logging statement, the model is asked to automated generate a logging statement.

statement quality. The result of LLM judge further supports the high quality of SOLM-generated statements.

RQ4: Can SOLMs generalize logging statement generation across diverse code repositories? Logging practices vary across projects. Evaluating SOLM generalization ability on diverse repositories ensures their applicability in real-world development environment.

Result. SOLMs demonstrate strong generalization capabilities in automated logging statement generation, maintaining high performance across diverse, unseen repositories. Similar logging practices, such as those shared among Apache open-source projects, significantly improve the cross-project generalization ability of SOLMs.

Contributions. To sum up, in this paper, we make the following contributions:

- We conduct the first large-scale empirical study to investigate the capability of SOLMs for automated logging statement generation, which demonstrating their capability to produce contextually and syntactically correct logging statement comparable to existing methods and LLMs.
- We explore parameter-efficient fine-tuning techniques that enhance SOLM performance while largely reducing computational cost, thus enabling effective fine-tuning on limited resources.
- We demonstrate SOLMs' generalization and practical advantages. SOLMs exhibit strong generalization across diverse, unseen code repositories, while their local deployment capability ensures privacy and aligns with sustainable computing goals.
- We make the source code, dataset, and results of our study publicly available [54] to benefit both practitioners and researchers in the field of automated logging statement generation.

Paper Organizations. Section 2 discusses the background. Section 3 describes the experimental design of our study. Section 4 presents the experimental results. Section 5 introduces the advantages of using SOLMs for automated logging statement generation and potential future work directions. Section 6 discusses threats to validity. Section 7 introduces the related work. Section 8 concludes the paper.

2 Background

2.1 Problem Definition

This paper focuses on the automated logging statement generation task (i.e., where-to-log + what-to-log), which to some extent can be viewed as a code editing problem: when presented with lines of code, usually corresponding to a method, the generator's task is to identify both the precise location for logging, referred to as the logging point, and the complete logging statement (i.e., level, variables, and text). The predicted logging point should match the one that was originally present in the source file before being removed, and the predicted logging statement itself should closely resemble the excised original. Figure 1 provides a visual example of this task, showing how a proficient logging statement generator would intelligently incorporate `LOG.info("Generating " + totalRows + " using " + numSplits);` at line 4. It is important to highlight that this task is distinctly separate from the comprehensive empirical investigation conducted by Li et al. [35], which predominantly examines the question of what-to-log but lacks the consideration of where-to-log.

2.2 Large Language Models

The evolution of language models in recent times can be divided into three transformative phases. Initially, there were neural language models (NLMs), followed by the phase of pre-trained language models (PLMs), and the current era sees the prominence of LLMs. Pre-trained models such as CodeT5 [65] and PLBART [1] have achieved noteworthy success in software engineering applications primarily due to task-specific pre-training processes. However, large language models have brought about a revolutionary change in the field due to their immense parameter counts, often exceeding 10 billion, and their comprehensive pre-training data. These models, unlike their pre-training predecessors, exhibit emergent capabilities that allow them to achieve robust performance across a wide range of tasks without necessitating pre-training tailored to specific tasks [11]. This quality substantially diminishes the requirement for resource-heavy training sessions. Within the realm of software engineering, large language models are mainly categorized into two groups. Unified large language models, such as GPT-4o and LLaMA, which are designed to integrate natural language and code corpora, whereas code-specific large language models, like StarCoder [33] and CodeLlama [58], are developed for specialization in tasks centered around coding.

Current methodologies for leveraging LLMs fall into two paradigms: prompt-based and tuning-based. Prompt-based methods exploit the zero-shot or few-shot capabilities of massive LLMs (e.g., GPT-4) through carefully engineered prompts, avoiding the need for explicit training data. They use techniques such as in-context learning (ICL) and chain-of-thought (COT). Conversely, fine-tuning approaches focus on parameter-efficient adaptation (e.g., prompt tuning, prefix tuning, and low-rank adaptation) to tailor smaller-scale LLMs for domain-specific tasks. These techniques freeze base model parameters while training minimal additional components, achieving performance comparable to full-parameter tuning at reduced computational costs.

2.3 LLM Applications in Software Engineering Task

Researchers have conducted in-depth investigations into the use of Large Language Models (LLMs) in a variety of software engineering tasks, including but not limited to code completion [22, 23], vulnerability detection [61, 80], program repair [40, 66], and test generation [5, 44]. These studies highlight the versatility and adaptability of LLMs in effectively tackling a range of software engineering challenges.

In certain tasks, approaches that utilize prompts have been shown to yield superior outcomes [21]. Pan et al., for instance, studied the efficiency of LLMs in the context of code translation [51]. Within

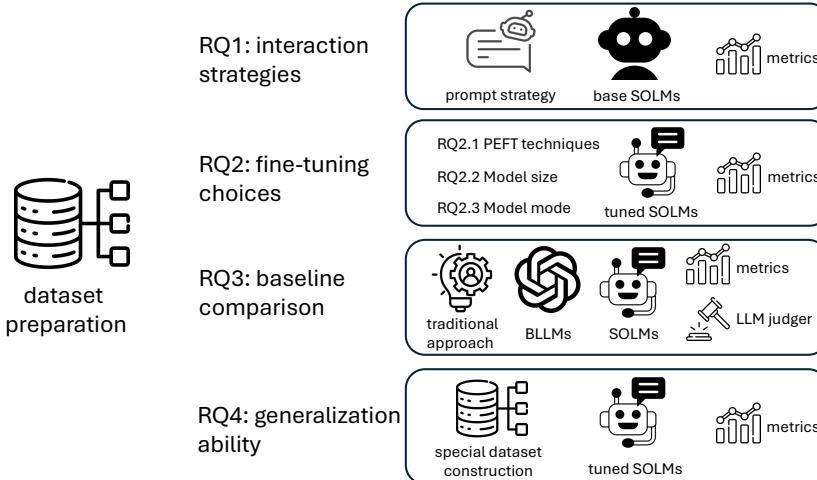


Fig. 2. The overview of our experimental design with four research questions.

the range of models assessed, which encompassed both SOLMs and GPT-4, the top-performing SOLM, known as StarCoder, managed to reach a successful translation rate of 14.5%, in contrast to the success rate of 47.3% achieved by GPT-4. In contrast, SOLMs have been shown to achieve comparable outcomes in specific domains. For instance, Tian et al. [63] observed an F1-score of 86.58% using UniXCoder for the task of detecting equivalent mutants, providing a notable contrast to the performance of GPT-4, which recorded an F1-score of approximately 55.90%. Furthermore, when employing Vicuna 13B in conjunction with the innovative LogPrompt strategy, the performance was found to be on par with that of GPT-4, as reported in [43].

3 Experimental Design

Figure 2 illustrates the overview of our study design. Initially, based on the AL-Bench dataset [62], we construct the fine-tuning, valid and test datasets. Then we investigate SOLMs for automated logging statement generation through four research questions. RQ1 seek to identify the most effective interaction strategies for using SOLMs in this task. RQ2 aims to determine the optimal fine-tuning strategies by PEFT techniques, model sizes, and model types. Following that, RQ3 compares the performance of fine-tuned SOLMs against existing specialized methods and LLM baselines. Finally, RQ4 assesses the ability of SOLMs to generalize their logging statement generation capabilities across diverse and unseen code repositories.

3.1 Dataset Preparation

3.1.1 Studied dataset. To evaluate the performance of automated logging statement generation, we select the most recently proposed AL-Bench [62]. This dataset, containing 42,224 logging statements from 10 widely used projects, was specifically constructed using stringent criteria (e.g., $\geq 10k$ stars, $\geq 1k$ logging statements, ≥ 500 log-related issues per project) to ensure the inclusion of well-maintained repositories where developers prioritize high-quality logging statements. Furthermore, AL-Bench intentionally incorporates projects from diverse domains—such as database management, task scheduling, distributed systems, messaging, and IoT platforms—to ensure comprehensive coverage of various real-world logging requirements and practices, making it a robust benchmark. Measures like using recent project versions and standardized code formatting were also employed

Table 1. Statistics of source repositories of AL-Bench [62].

Index	Dataset	Domains	#Stars	#Forks	#LOLS
R1	Dbeaver	Database Management	43.3k	3.7k	1.7k
R2	Dolphinscheduler	Task Scheduling	13.5k	4.8k	1.9k
R3	Doris	High Performance Database	13.6k	3.4k	2.9k
R4	Flink	Data Processing	24.8k	13.5k	3.2k
R5	Hadoop	Distributed Storage	15.1k	9.0k	16.0k
R6	Kafka	Messaging Systems	30.0k	14.3k	3.4k
R7	Keycloak	Identity and Access Management	26.9k	7.2k	1.0k
R8	Pulsar	Messaging Systems	14.6k	3.6k	7.2k
R9	Thingsboard	IoT Platform	18.7k	5.5k	2.7k
R10	Zookeeper	Distributed Coordination	12.5k	7.3k	1.9k

during its creation to mitigate potential data contamination risks from pre-training corpora. Table 1 provides further statistical details on these source repositories.

3.1.2 Pre-processing and dataset construction. To align with the research objectives of this study and accommodate the requirements of certain baseline models, we performed several adjustments to the original dataset. Firstly, recognizing that some baseline models have an input token limit, we filtered out data instances where the input code exceeded 512 tokens. Secondly, the original construction of AL-Bench could generate multiple data points from a single Java function if it contained multiple logging statements, with each data point representing one specific automated logging statement generation case. To prevent potential data leakage, where highly similar code snippets from the same source file might inadvertently appear across different dataset splits (e.g., fine-tuning and testing), we implemented a file-level splitting strategy. This approach ensures that all data instances originating from the same Java file are strictly allocated to only one of the fine-tuning, validation, or test sets. After applying these pre-processing steps, we obtained a final dataset comprising 33,224 instances. We then partitioned this dataset into fine-tuning, validation, and test sets, targeting an 8:1:1 ratio. Because our file-level splitting strategy required keeping all instances from a single file within the same set, the resulting distribution was approximate. The final fine-tuning set contains 26,713 instances, the validation set contains 3,508 instances, and the test set contains 3,003 instances.

3.2 Studied Models

In our study, we investigate the performance of the following SOLMs for logging statement generation. These models have been widely adopted in the literature related to SE tasks, including:

- **LLaMA** [12] is Meta’s latest LLM and refines the Llama 2 framework. It stands as a prominent open source LLM used in numerous software applications. Trained on an extensive and varied dataset far surpassing its predecessor, Llama 3 exhibits significantly improved proficiency in reasoning, code generation, and instruction adherence.
- **Mistral** [25] is noted for its efficiency and performance, utilizing Grouped-Query Attention (GQA) and Sliding Window Attention (SWA) for faster inference and broader context handling, and demonstrates robust general abilities and notable coding skills.
- **CodeLlama** [58] is a series of LLMs specialized in generating and completing code, based on the Llama2 framework. These models are initially trained using a dataset of 500 billion code tokens and subsequently refined to manage extended context effectively.

- **Qwen2.5-coder** [20] is a code-specialized version of the Qwen2 [69] family, which inherits Qwen's multilingual capabilities and architectural improvement. While demonstrating strong and comprehensive coding abilities, it also possesses good general and mathematical skills.

3.3 Baselines

To evaluate SOLMs performance, we selected the baselines by conducting a literature review of relevant papers published in SE venues. From this, we find the following four methods for evaluation: **LANCE** [48], **LEONID** [47], **UniLog** [68], and **FastLog** [67]. Additionally, we examine several notable LLM baselines, including general-purpose LLMs (**Claude3.7-sonnet**, **GPT4o**, **LLAMA-405b**), and a code-specific LLM (**Deepseek-coder-v3**). In relation to the methodologies for prompting, we derive our approach from the study [10] and incorporate four different strategies: instruction prompting (**base**), in-context learning (**ICL**), retrieval-augmented generation (**RAG**) and chain of thought (**CoT**). The instruction prompting strategy involves directly prompting LLMs to generate logging statements using identical inputs as those provided to SOLMs, without any supplementary data. The ICL approach consists of providing one random example before the main query to assist the model in grasping the nature of the task more effectively. In the RAG approach, rather than selecting example randomly, we retrieve precise examples from the valid dataset to accommodate various input samples. We specifically employ the BM25 algorithm to identify the case within the valid dataset that most closely resembles the query sample in terms of similarity. The details of the prompts are shown in Figure 3.

3.4 Strategies for Parameter-Efficient Fine-Tuning

We examined how different PEFT strategies influence the performance of SOLMs when generating automated logging statements.

Prefix tuning [34], is a PEFT strategy designed to adapt LLMs to specific downstream tasks while keeping the original model parameters entirely frozen. Instead of modifying the model's weights, it introduces a small set of trainable continuous vectors, known as the "prefix", which are prepended to the key and value sequences within the multi-head attention mechanisms of the Transformer architecture, typically applied to the topmost L layers. Specifically, for a given layer l , trainable prefix matrices $\mathbf{P}_k \in \mathbb{R}^{K \times C}$ and $\mathbf{P}_v \in \mathbb{R}^{K \times C}$ (where K is the prefix length, a key hyperparameter, and C is the hidden dimension) are concatenated with the original key ($\mathbf{K}_l \in \mathbb{R}^{M \times C}$) and value ($\mathbf{V}_l \in \mathbb{R}^{M \times C}$) matrices derived from the M input tokens, forming augmented matrices $\mathbf{K}'_l = [\mathbf{P}_k; \mathbf{K}_l]$ and $\mathbf{V}'_l = [\mathbf{P}_v; \mathbf{V}_l]$. During fine-tuning, only the parameters comprising these prefix matrices ($\mathbf{P}_k, \mathbf{P}_v$ across the selected layers) are optimized via gradient descent, learning task-specific representations that effectively steer the frozen model's attention and subsequent computations towards generating appropriate outputs for the target task. This approach significantly reduces the number of trainable parameters compared to full fine-tuning, requires storing only the small prefix parameters per task, and avoids catastrophic forgetting by leaving the core model untouched.

Prompt tuning [29] offers an even more lightweight approach by confining trainable parameters exclusively to continuous prompt embeddings added only at the input layer, while freezing the entire pre-trained model, including its word embedding table. This method prepends a sequence of K learnable prompt embeddings, represented by a single trainable matrix $\mathbf{P}_{\text{emb}} \in \mathbb{R}^{K \times C}$ (where K is the prompt length and C is the model's embedding dimension), to the original sequence of M input token embeddings $\mathbf{E} \in \mathbb{R}^{M \times C}$, yielding an augmented input sequence $\mathbf{E}' = [\mathbf{P}_{\text{emb}}; \mathbf{E}]$. This combined sequence \mathbf{E}' is then fed directly into the first layer of the frozen Transformer backbone. During the fine-tuning process, only the parameters of the prompt embedding matrix \mathbf{P}_{emb} are updated. The core idea is that these learned continuous vectors act as a "soft prompt" or task instruction,

conditioning the frozen model’s behavior without requiring any internal modifications. Prompt Tuning demonstrates significant efficiency regarding parameter usage, typically necessitating the update of fewer than 0.1% of the total model parameters. This characteristic renders it highly efficient in terms of both storage and computation, especially in multi-task contexts.

Lora [19] provides a distinct PEFT mechanism based on the hypothesis that the change in weights during model adaptation has a low intrinsic rank. Instead of adding prefix or prompt tokens, LoRA freezes the original pre-trained weights $\mathbf{W}_0 \in \mathbb{R}^{d \times k}$ of selected layers (commonly the query, key, value, and output projection matrices in self-attention, and sometimes feed-forward layers) and injects trainable, rank-decomposition matrices in parallel. Specifically, the weight update $\Delta\mathbf{W}$ is approximated by the product of two smaller, low-rank matrices: $\mathbf{W}_{\text{down}} \in \mathbb{R}^{d \times r}$ and $\mathbf{W}_{\text{up}} \in \mathbb{R}^{r \times k}$, where the rank r is a crucial hyperparameter significantly smaller than the original dimensions ($r \ll \min(d, k)$). The modified forward pass for an input \mathbf{x} computes the output as the sum of the original path and the adapter path: $\mathbf{h}_{\text{adapted}} = \mathbf{W}_0\mathbf{x} + \Delta\mathbf{W}\mathbf{x} = \mathbf{W}_0\mathbf{x} + \alpha(\mathbf{W}_{\text{down}}\mathbf{W}_{\text{up}})\mathbf{x}$, where α is often a constant scaling factor (like α/r). During fine-tuning, only the parameters of \mathbf{W}_{down} (typically initialized randomly) and \mathbf{W}_{up} (typically initialized to zero) are optimized. A significant advantage of LoRA is that the learned adapter weights can be mathematically merged with the original weights ($\mathbf{W} = \mathbf{W}_0 + \mathbf{W}_{\text{down}}\mathbf{W}_{\text{up}}$) after training, resulting in a single weight matrix per adapted layer and incurring zero additional inference latency compared to the original model, while still offering substantial parameter savings during training and allowing easy task switching by loading different adapter pairs.

QLora [7] represents a significant advancement in memory-efficient fine-tuning, specifically designed to make the adaptation of extremely large language models feasible on commodity hardware with limited VRAM. It ingeniously combines low-precision quantization of the base model with the LoRA technique. The core strategy involves loading the massive pre-trained base model \mathbf{W}_0 with its weights quantized to a very low bit-format, most notably 4-bit NormalFloat (NF4), a data type empirically shown to be effective for normally distributed weights, and keeping these quantized weights $Q(\mathbf{W}_0)$ frozen. Standard LoRA adapters, consisting of low-rank matrices \mathbf{W}_{down} and \mathbf{W}_{up} , are then introduced parallel to these quantized layers, but crucially, these adapter weights are maintained and trained in a higher precision format, typically BFloat16, to preserve adaptation capacity. The forward pass thus involves computations using the low-precision base model and the higher-precision adapters: $\mathbf{h}_{\text{adapted}} \approx Q(\mathbf{W}_0)\mathbf{x} + \alpha(\mathbf{W}_{\text{down}}\mathbf{W}_{\text{up}})\mathbf{x}$. To further minimize memory bottlenecks, QLoRA incorporates innovations like double quantization and paged optimizers. By drastically reducing the memory footprint of the base model weights, activations (due to lower precision), and optimizer states, QLoRA enables fine-tuning models with tens or hundreds of billions of parameters on single consumer GPUs, while aiming to retain the task performance levels achieved by full-precision LoRA.

3.5 Evaluation Metrics

Considering earlier research [35, 62], we assess the performance of automated generation of logging statements by focusing on four aspects: the logging point, the logging levels, the logging text, and the logging variables. While each of these components highlights distinct aspects of system runtime information, they collectively serve as essential and complementary resources that aid engineers in analyzing and understanding system behaviour.

3.5.1 Logging point. Position Accuracy (PA): To quantify PA, we compare the predicted locations of logging statements against their ground truth positions in the source code. This metric is formally defined as the ratio of correctly positioned logging statements ($LS_{\text{position_correct}}$) to the total number of logging statements (LS_{all}), expressed as $\frac{LS_{\text{position_correct}}}{LS_{\text{all}}}$.

3.5.2 Logging level. We use the Level Accuracy (LA) and Average Ordinal Distance Score (AOD) for evaluating the prediction of logging levels. Given the significant semantic differences between these levels and their implications for system monitoring and maintenance, we rigorously assess LA by comparing predicted log levels against their ground truth values in the source code. This metric is formally defined as the ratio of correctly predicted log levels ($LS_{level_correct}$) to the total number of logging statements (LS_{all}), expressed as $\frac{LS_{level_correct}}{LS_{all}}$. AOD evaluates how closely the current logging level aligns with the recommended logging level for each specific logging statement, as detailed in [38]. The formula to calculate AOD is given by: $AOD = \frac{\sum_{i=1}^N (1 - \frac{Dis(a_i, s_i)}{MaxDis(a_i)})}{N}$, where N represents the total number of logging statements in consideration. The term $MaxDis(a_i)$ is used to denote the maximum potential distance for the actual log level a_i .

3.5.3 Static logging text. Same as previous study [8, 35, 48], our evaluation of static logging texts is conducted through the application of two metrics commonly employed in the domain of machine translation: BLEU [52] and ROUGE [41]. These metrics, grounded in n-gram analysis, are instrumental in assessing the degree of similarity between log messages that are generated computationally and those authored by developers. They provide a normalized score continuum from 0 to 1, with elevated scores indicative of a closer resemblance. In our methodology, we specifically implement various forms of these metrics, identified as BLEU-4 and ROUGE-L.

3.5.4 Dynamic logging variables. We use Precisely Match Rate (PMR) and F1 to evaluate dynamic logging variables. PMR ensures consistency in the capture of variable runtime data—a critical aspect of log effectiveness. We extract dynamic variables from both reference implementations and predicted logging statements, then perform exact matching to evaluate correspondence. PMR is formally defined as the ratio of exactly matched dynamic variables ($LS_{variable_correct}$) to the total number of logging statements (LS_{all}), expressed as $\frac{LS_{variable_correct}}{LS_{all}}$. Moreover, consider each logging statement and let us define S_{ud} as the set of variables included in the generated logging statement, while S_{gt} pertains to the set of variables present in the actual logging statement. In our analysis, we determine and present the following metrics: the precision, which is the ratio of variables from the updates that accurately match those in the actual logging ($precision = \frac{S_{ud} \cap S_{gt}}{S_{ud}}$); the recall, which indicates the fraction of actual variables correctly anticipated by the model ($recall = \frac{S_{ud} \cap S_{gt}}{S_{gt}}$); and, lastly, their harmonic mean, expressed as the F1 score ($F_1 = 2 * \frac{Precision * Recall}{Precision + Recall}$) [35].

3.6 LLM-as-a-judge

The evaluation of automatically generated logging statements, drawing upon our experimental findings and established prior work, conventionally proceeds by assessing distinct modules such as placement, verbosity level, and textual content. However, it is increasingly evident that certain prevalent metrics do not adequately capture the nuanced performance aspects of generated logging statements [13, 57]. For instance, in the assessment of static text components, metrics like BLEU-4 and ROUGE-L are confined to lexical similarity, largely overlooking crucial semantic congruity. This limitation presents a formidable challenge in establishing a unified and robust methodology for evaluating the overall quality of automatically generated logging statements.

Recently, research within the NLP domain has explored the application of LLM to appraise the quality of LLM-generated content, known as "LLM-as-a-judge". While human evaluation remains a reliable way, its inherent drawbacks of being time-consuming and cost-intensive run counter to the objectives of automated evaluation. Consequently, researchers are increasingly investigating methods to prompt or train LLMs to align with human evaluative preferences, thereby offering a scalable alternative to manual assessment. Supporting this direction, an empirical study by Wang et

al. [64] has demonstrated the efficacy of the LLM-as-a-judge approach across various SE tasks. Their findings indicate that output-based evaluation methods, when coupled with state-of-the-art LLMs, yield optimal performance irrespective of the specific inference strategies employed. Informed by these advancements, this paper adopts the LLM-as-a-judge methodology to augment the quality assessment of automatically generated logging statements.

Specifically, we select three LLMs recognized for their superior performance in code-related tasks: Claude3.7-Sonnet, Deepseek-coder-v3, and GPT-4o. We choose this model due to their robust code comprehension and generation capabilities, which are critical for assessing the nuanced quality of logging statements. The evaluation process involves providing each LLM judge with the input code context, the generated logging statement from model, and the corresponding ground truth logging statement. The judges assign scores ranging from 0 to 3, where higher scores indicate greater alignment with the ground truth in terms of logging point accuracy, level appropriateness, static text quality, and dynamic variable correctness. To ensure consistency and reliability, we develop a comprehensive scoring guideline, which outline specific criteria for evaluating each component of the logging statement. These criteria address syntactic accuracy, semantic relevance, and contextual appropriateness, mitigating the limitations of traditional metrics like BLEU-4 and ROUGE-L.

Score Guideline

0: (Unacceptable) The logging statement is syntactically incorrect or misplaced. Formatting deviates significantly, and code changes may impair functionality or maintainability.

1: (Significant Issues) The statement is syntactically correct and appropriately placed but has major flaws: vague static text, incorrect log level, or missing key variables. Formatting inconsistencies or minor code alterations reduce readability but preserve functionality.

2: (Mostly Correct with Minor Flaws) The statement is semantically accurate, includes most relevant details, and uses an appropriate log level. Minor issues include verbose text, suboptimal formatting, or slight stylistic deviations. Functionality is preserved with trivial changes.

3: (Highly Accurate) The statement is precise, concise, and matches the ground truth. It uses the correct log level, parameterized logging, and consistent styling. The code retains full functionality and maintainability.

3.7 Implementation details

To evaluate conventional logging approaches and LLMs, we reproduced conventional methods using replication packages provided by their authors. For LLMs, we generated logging statements by calling their official APIs, setting the temperature to 0 to ensure deterministic outputs for identical queries, thus guaranteeing reproducibility. For SOLMs, we performed fine-tuning for one epoch on a dedicated dataset, using a batch size of 64 and a learning rate of 1e-4. All experiments, including training, fine-tuning, and inference, were conducted on a single NVIDIA A100 80GB GPU provided by Modal [50], a serverless cloud infrastructure platform that supports easy deployment and reproducibility through provided scripts. Detailed experimental settings are available in our replication package [54].

4 Experimental Results

4.1 RQ1: What are the most effective interaction strategies for using SOLMs in logging generation?

Motivation. Initially, our objective is to determine if the manner in which we engage with the model during the inference phase can have a profound effect on its success in generating automated

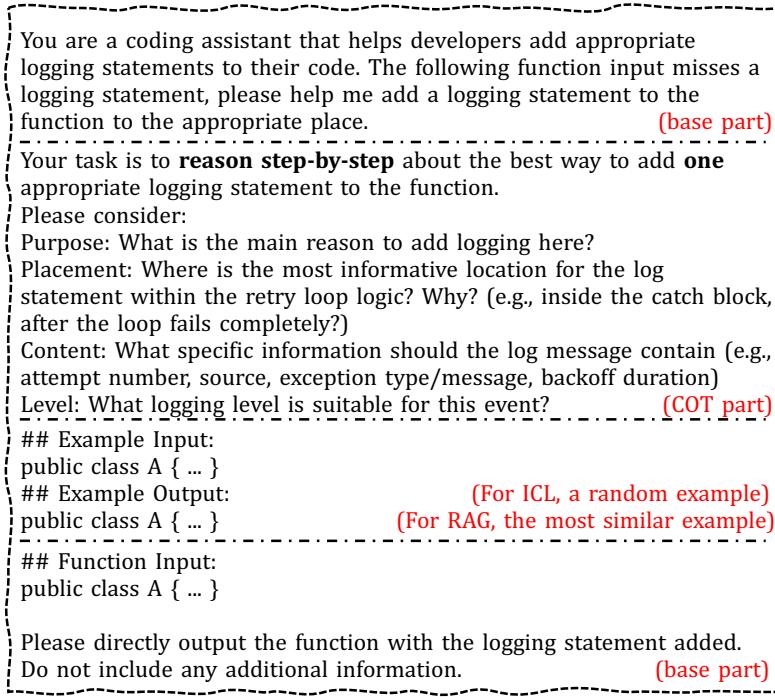


Fig. 3. The prompt template for automated logging statement generation.

logging statements. The structuring of the input prompt plays a crucial role in shaping how the SOLM interprets the given task and how it subsequently produces its outputs.

Approach. In addressing this question, our study is focused on evaluating the effectiveness of current prompting techniques within the domain of log generation. We specifically analyze, based on the definitions laid out in Section 3.3, the effectiveness of several prompting strategies: basic instruction prompting (**base**), in-context learning (**ICL**), retrieval-augmented generation (**RAG**), and chain-of-thought (**CoT**). The specific details regarding the prompt templates used can be found in Figure 3. To strengthen the generalizability of our findings, we employ multiple 7B instruction-following models, namely LLaMA, Mistral, CodeLlama, and Qwen2.5-Coder, all in their original, un-fine-tuned configurations.

Results. The quantitative evaluation comparing the four prompting techniques across the four selected 7B SOLMs is presented in Table 2. Our analysis of these results yields two primary findings concerning the performance of un-fine-tuned models and the efficacy of different interaction strategies for automated logging generation.

First, we observe a distinct performance disparity between the general-purpose instruction-following models (LLaMA, Mistral) and the code-specific models (CodeLlama, Qwen2.5Coder) when used without any task-specific fine-tuning. The general-purpose models generally demonstrate superior performance on this task. For instance, LLaMA and Mistral achieve peak PA scores of 21.01 and 18.15 respectively (both using RAG), substantially higher than the peak PA scores achieved by CodeLlama (11.62 with ICL) and Qwen2.5Coder (13.25 with CoT). We attribute this overall trend to the relatively weaker instruction-following capabilities observed in the un-fine-tuned code-specific models for this specific task. We noted a higher tendency for CodeLlama and

Qwen2.5Coder to refuse the prompt or return non-parsable empty responses compared to LLaMA and Mistral, which negatively impacts their effectiveness in this experimental setting. This suggests that, without fine-tuning, the broader instruction comprehension of general-purpose models may be more advantageous for complex code-related generation tasks like automated logging statement generation than the specialized but potentially more rigid capabilities of un-fine-tuned code models.

Findings 1: Without fine-tuning, general-purpose models outperform code-specific models for automated logging statement generation due to the former's better instruction following ability.

Second, RAG emerges as the most effective prompting technique for enhancing automated logging generation performance. While other techniques occasionally yield the top score for an isolated metric, RAG demonstrates the most significant and robust improvements across the majority of metrics and models. Notably, for Mistral, RAG achieves the highest scores across all evaluated metrics, including PA (18.15), F1 (40.21), and ROUGE-L (34.74). For LLaMA, RAG secures the top performance in PA (21.01), PMR (41.68), F1 (46.28), BLEU-4 (15.95), and ROUGE-L (36.73). For CodeLlama and Qwen2.5Coder, RAG generally leads to substantial gains over the baseline, particularly in metrics like F1 (CodeLlama: 39.01, Qwen2.5Coder: 49.28) and ROUGE-L (CodeLlama: 34.36, Qwen2.5Coder: 37.57). These results strongly indicate that providing relevant contextual information retrieved from a knowledge base significantly aids the SOLMs in accurately determining where to log, what variables to include, and formulating appropriate log messages, making RAG a highly promising strategy.

Findings 2: RAG proves the most effective prompting technique, significantly enhancing automated logging statement generation performance across models and metrics.

4.2 RQ2: What's the best strategy using SOLMs for automated logging statement generation?

Motivation. In the course of the fine-tuning operation, a diverse array of strategies has the potential to influence the efficacy of our tasks significantly. In order to systematically assess the capabilities of the SOLMs, we thoroughly investigate the following factors:

(RQ2.1) Which PEFT technique yields the optimal performance for automated logging statement generation using SOLMs? While SOLMs are more compact than their larger counterparts, fully fine-tuning them for specific downstream tasks like automated logging statement generation can still be computationally demanding and may risk overfitting, especially with limited task-specific data. PEFT methodologies have emerged as a compelling solution, enabling adaptation by updating only a small fraction of the model's parameters or by adding a small set of new, trainable parameters. This significantly reduces computational costs and the risk of catastrophic forgetting of the model's pre-trained knowledge. However, a diverse range of PEFT techniques exists, each employing different mechanisms to inject task-specific information into the SOLM. The relative efficacy of these techniques can vary depending on the nature of the downstream task. For logging statement generation, which involves understanding code context, identifying appropriate logging locations, and generating relevant log messages, it is unclear which PEFT strategy offers the optimal balance of performance and efficiency. Therefore, we conduct an evaluation of the performance of SOLMs fine-tuned with various prominent PEFT techniques to ascertain which techniques yield superior performance outcomes.

(RQ2.2) How does the size of SOLMs impact the performance-resource trade-offs in automated logging statement generation? The number of parameters in a language model is a critical factor that typically dictates its representational ability, learning capacity, and consequently, its performance

Table 2. Comparison of prompting techniques for automated logging generation using four 7B instruction-following SOLMs.

Model	Techs	Location		Level		Variable		Text	
		PA	LA	AOD	PMR	F1	BLEU-4	ROUGE-L	
LLAMA	base	13.32	54.50	83.06	38.00	30.41	9.68	28.92	
	ICL	9.99	50.67	81.25	30.00	30.95	11.31	30.60	
	RAG	21.01	53.72	82.09	41.68	46.28	15.95	36.73	
	COT	6.16	28.65	72.64	10.27	19.15	6.96	23.49	
Mistral	base	12.85	46.89	79.86	25.13	23.70	9.91	27.19	
	ICL	11.99	40.56	77.08	31.11	28.78	8.05	26.26	
	RAG	18.15	65.14	86.35	37.25	40.21	14.36	34.74	
	COT	6.63	50.25	79.23	13.57	21.02	11.01	30.35	
CodeLLAMA	base	6.99	57.14	84.29	37.62	35.74	12.21	31.71	
	ICL	11.62	48.14	79.87	26.36	29.47	9.50	27.54	
	RAG	8.16	62.04	86.43	31.02	39.01	13.82	34.36	
	COT	5.06	47.37	82.09	20.39	35.63	11.44	29.49	
Qwen2.5Coder	base	4.30	58.91	83.14	27.91	29.55	8.61	27.13	
	ICL	2.03	45.90	78.69	36.07	43.50	8.64	31.21	
	RAG	3.40	59.80	83.33	45.10	49.28	15.10	37.57	
	COT	13.25	51.01	80.21	20.35	48.66	10.58	29.52	

on downstream tasks. Although we focus on SOLMs, there is still considerable variation in size within this class. Larger models might capture more complex code patterns and nuances relevant to logging, potentially leading to higher accuracy, but they also incur greater computational costs during fine-tuning and inference. Therefore, evaluating the impact of model size is essential to understand the performance-resource trade-offs specific to automated logging statement generation.

(RQ2.3) Does the instruct variant of a SOLM outperform its base counterpart for automated logging statement generation? The distinction between using a ‘base’ pre-trained model versus an ‘instruct’ version of an SOLM presents another critical strategic choice. Instruct models are specifically optimized to understand and respond to user prompts and instructions, which could be beneficial for a directed task. They might more readily produce outputs that adhere to desired formats or incorporate specified information. However, this instruction tuning is often general-purpose. Base models, on the other hand, represent the raw capabilities learned during pre-training and might offer greater plasticity when fine-tuned on a highly specific downstream task like ours. It is plausible that fine-tuning a base model directly on logging data could lead to a more specialized and potentially more effective model, whereas an instruct model might carry over behaviors from its instruction-tuning phase that are not optimally aligned with logging generation. Therefore, we aim to clarify which model mode serves as a better foundation for this task.

Approach. To address RQ2.1, we selected the 7B parameter versions of all four SOLMs as our primary subjects for investigating the impact of different PEFT techniques. We systematically evaluated four prominent PEFT methods: Prefix Tuning, Prompt Tuning, LoRA, and QLoRA. To establish a comparative baseline, we also measured the performance using direct inference without any PEFT fine-tuning (referred to as ‘base’). For all experiments conducted under RQ2.1, including

Table 3. Performance Comparison of PEFT Techniques for SOLMs in Automated Logging Statement Generation.

Model	PEFT Techs	Location		Level		Variable		Text	
		PA	LA	AOD	PMR	F1	BLEU-4	ROUGE-L	
LLaMA	base	21.01	53.72	82.09	41.68	46.28	15.95	36.73	
	prefix tuning	20.98	57.46	83.59	37.94	45.27	14.42	35.71	
	prompt tuning	25.01	67.38	87.85	43.01	50.33	15.66	35.96	
	LoRA	56.84	63.56	87.37	50.15	58.22	19.84	40.89	
	QLoRA	45.27	57.18	83.56	44.66	51.29	15.97	36.60	
Mistral	base	18.15	65.14	86.35	37.25	40.21	14.36	34.74	
	prefix tuning	20.35	63.34	85.20	38.95	43.07	15.96	36.75	
	prompt tuning	31.87	60.92	85.41	43.68	53.59	17.81	38.36	
	LoRA	63.97	69.50	88.64	52.79	57.89	23.40	45.73	
	QLoRA	61.90	69.28	88.66	53.31	58.97	22.42	44.70	
CodeLlama	base	8.16	62.04	86.43	31.02	39.01	13.82	34.36	
	prefix tuning	16.35	62.12	86.07	41.14	42.43	17.19	38.48	
	prompt tuning	18.15	62.42	86.81	41.76	49.91	18.41	39.69	
	LoRA	59.01	68.57	88.74	52.77	59.10	23.10	44.92	
	QLoRA	58.97	68.27	88.62	52.00	58.12	22.30	44.48	
Qwen2.5Coder	base	3.40	59.80	83.33	45.10	49.28	15.10	37.57	
	prefix tuning	25.27	65.48	87.80	44.14	56.36	15.23	35.47	
	prompt tuning	30.04	67.63	88.01	46.12	54.63	18.80	38.74	
	LoRA	62.40	68.46	88.82	52.24	58.98	23.04	44.96	
	QLoRA	60.21	67.87	88.70	51.55	59.47	22.52	44.03	

the baseline, we consistently utilized the RAG-enhanced prompt format that has been identified as effective during our experiment in RQ1.

For RQ2.2, focusing on the influence of model size, we selected the Qwen2.5 Coder model series. This choice is driven by the public availability of multiple versions within the same model family, specifically those with 0.5B, 1.5B, 3B, 7B, and 14B parameters, enabling a controlled comparison. Based on the findings from RQ2.1 where LoRA demonstrated superior performance among the PEFT techniques, we exclusively employ LoRA for fine-tuning across these different model sizes. Furthermore, we evaluate each size using both the basic prompt ('base') and the RAG-enhanced prompt ('RAG'), in order to explore whether the effectiveness of RAG varies with model scale, particularly to assess the RAG capabilities of the smaller SOLMs.

To address RQ2.3, we compare the performance of 'base' models against their 'instruct' counterparts for automated logging statement generation. We select the Mistral 7B model, available in both base and instruct variants, for a controlled comparison, as it got the best performance in RQ2.1. Both model modes are fine-tuned using LoRA and employed the RAG-enhanced prompt, consistent with the result of RQ2.1 and RQ2.2. The fine-tuning process spanned five epochs, and performance are evaluated using metrics including Reject Rate, PA, LA, AOD, PMR, F1, BLEU-4, and ROUGE-L. The Reject Rate, defined as the percentage of test set examples rejected by the fine-tuned model during inference due to misalignment with learned task-specific criteria, quantifies the model's selectivity, reflecting its ability to adhere to prompt instructions and generate valid logging statements.

Results. (RQ2.1) Table 3 shows the performance comparison of PEFT techniques for SOLMs in automated logging statement generation. We find that all evaluated PEFT methods consistently

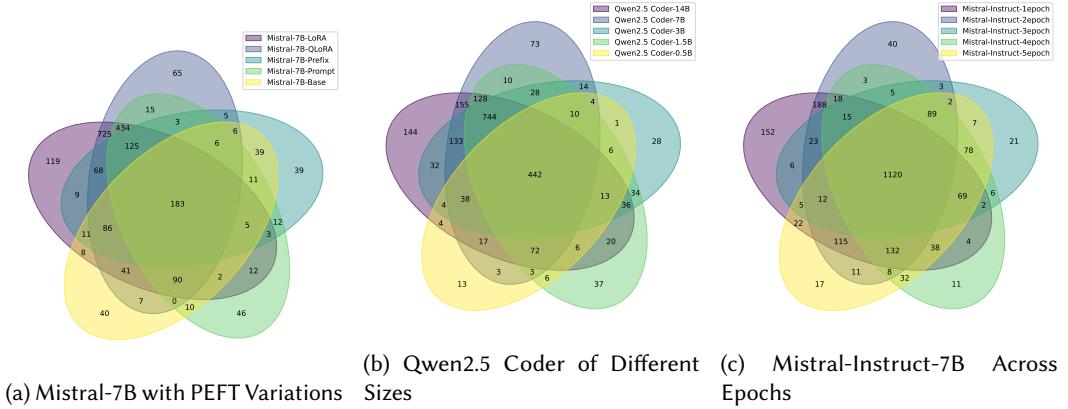


Fig. 4. Overlap of Corrected Logging Statement Placement Across Different SOLM Configurations.

improve performance over the baseline across all SOLMs and most metrics. For instance, looking at the prediction accuracy, QLoRA fine-tuning increased PA from 13.32 to 45.27 for LLaMA, from 12.85 to 61.90 for Mistral, from 6.99 to 58.97 for CodeLlama, and from 4.30 to 60.21 for Qwen2.5Coder. Similar substantial gains are observed across other metrics like F1 score for variable prediction and BLEU-4/ROUGE-L for statement generation, indicating that fine-tuning with parameter-efficient techniques, is crucial for adapting SOLMs to this specific task.

Furthermore, LoRA generally emerges as the most effective PEFT methodology, closely followed by QLoRA. LoRA achieves the highest scores for the majority of metrics across all four models. For example, with LoRA, LLaMA gets the top PA (56.84), PMR (50.15), F1 (58.22), BLEU-4 (19.84), and ROUGE-L (40.89). Similarly, LoRA leads to the best PA (63.97), LA (69.50), BLEU-4 (23.40), and ROUGE-L (45.73) for Mistral. CodeLlama shows LoRA as the top performer across all metrics. For Qwen2.5Coder, LoRA is also dominant, securing the best PA (62.40), LA (68.46), AOD (88.82), PMR (52.24), BLEU-4 (23.04), and ROUGE-L (44.96). QLoRA consistently performs very competitively, often achieving the second-best results or even surpassing LoRA in a few specific instances (e.g., F1 for Qwen2.5Coder, PMR and F1 for Mistral). Prompt Tuning shows some strength, particularly for ‘level’ prediction with LLaMA, while Prefix Tuning, though an improvement over the baseline, is generally outperformed by LoRA, QLoRA, and Prompt Tuning.

Additionally, the venn diagram in Figure 4a illustrates the overlap of corrected logging statement placements across different PEFT variations for Mistral-7B. The largest overlap (183) is observed in the central region, indicating a core set of logging statements consistently corrected across all PEFT methods (base, Prefix Tuning, Prompt Tuning, LoRA, and QLoRA). LoRA and QLoRA show significant individual contributions (125 and 86, respectively), suggesting their effectiveness in identifying unique logging placements, while the base method contributes the least (40), highlighting the improvement brought by PEFT techniques.

Findings 3: Fine-tuning with PEFT techniques significantly enhances SOLMs performance for automated logging statement generation, with LoRA demonstrating the most consistent and superior results across the evaluated models and metrics.

(RQ2.2) Table 4 shows the impact of model size on performance and resource usage for automated logging statement generation. We can find that increasing model size generally leads to improved performance in automated logging statement generation, particularly for models 3B and larger.

Table 4. Impact of Model Size on Performance and Resource Usage for Automated Logging Statement Generation.

model params	trainable params	training time (s/epoch)	inference time (s/prompt)	PA	LA	AOD	PMR	F1	BLEU-4	ROUGE-L
0.5B	~281M	2438.2749	0.0959	21.38	61.53	86.78	41.74	56.59	18.95	39.55
1.5B	~485M	4395.2893	0.1866	53.11	60.69	85.70	50.34	58.39	20.35	40.69
3B	~652M	7694.3684	0.2375	52.18	68.41	88.77	49.20	56.94	22.23	43.18
7B	~1139M	13258.3642	0.2710	62.40	68.46	88.82	52.24	58.98	23.04	44.96
14B	~1625M	21780.5427	0.4854	66.20	69.92	89.36	54.53	59.93	25.20	47.22

Across almost all metrics, there is a discernible improvement as the model parameter count increases from 0.5B to 14B. For example, prediction accuracy (PA) improves from 21.38 (0.5B) to 66.20 (14B), and ROUGE-L scores for text generation increase from 39.55 (0.5B) to 47.22 (14B). The 14B model consistently outperforms all smaller variants, and the 7B model also shows strong performance.

Models smaller than 3B (i.e., 0.5B and 1.5B) exhibit less stable performance scaling. While the 0.5B model is generally the weakest, the progression to the 1.5B and then to the 3B model is not uniformly positive across all metrics. For instance, the 1.5B model shows a slight decrease in LA (60.69 vs 61.53 for 0.5B) and AOD (85.70 vs 86.78 for 0.5B). Furthermore, when moving from 1.5B to 3B, there are slight dips in PA (52.18 vs 53.11), PMR (49.20 vs 50.34), and F1 (56.94 vs 58.39). This suggests that while larger models generally perform better, the performance gains for models below 3B parameters might be less consistent or predictable for this specific task and fine-tuning approach.

Larger models come with increased resource requirements. As model size increases, the training time per epoch, and inference time per prompt also escalate substantially. For instance, training time per epoch rises from approximately 2438 seconds for the 0.5B model to 21780 seconds for the 14B model. Similarly, inference time per prompt increases from 0.0959 seconds (0.5B) to 0.4854 seconds (14B).

The venn diagram in Figure 4b depicts the overlap of corrected logging statement placements across different sizes of the Qwen2.5Coder model (0.5B, 1.5B, 3B, 7B, 14B). The central overlap (442) represents logging statements consistently corrected across all sizes, with the 14B model contributing the most unique placements (152), followed by 7B (73). Smaller models (0.5B and 1.5B) show limited unique contributions (21 and 6, respectively), reinforcing the finding that models with 3B+ parameters perform better for this task.

Findings 4: For models with 3B+ parameters, performance in generating logging statements improves with more parameters, but increases computational costs, indicating a performance-resource trade-off. Models under 3B show inconsistent scaling, suggesting a minimum capacity may needed for this task.

(RQ2.3) Figure 5 illustrates the performance comparison between the base and instruct variants of the Mistral-7B model across five epochs for automated logging statement generation. The instruct model consistently outperforms the base model across most metrics, including Reject Rate, PA, and ROUGE-L. For instance, the instruct model achieves a lower Reject Rate, indicating better adherence to task-specific criteria and fewer invalid outputs (Figure 5a). Similarly, the instruct model demonstrates higher PA (Figure 5b), reflecting superior accuracy in predicting logging statement placement. The ROUGE-L scores (Figure 5d) further confirm that the instruct model generates logging statements with greater textual similarity to the ground truth. These trends are

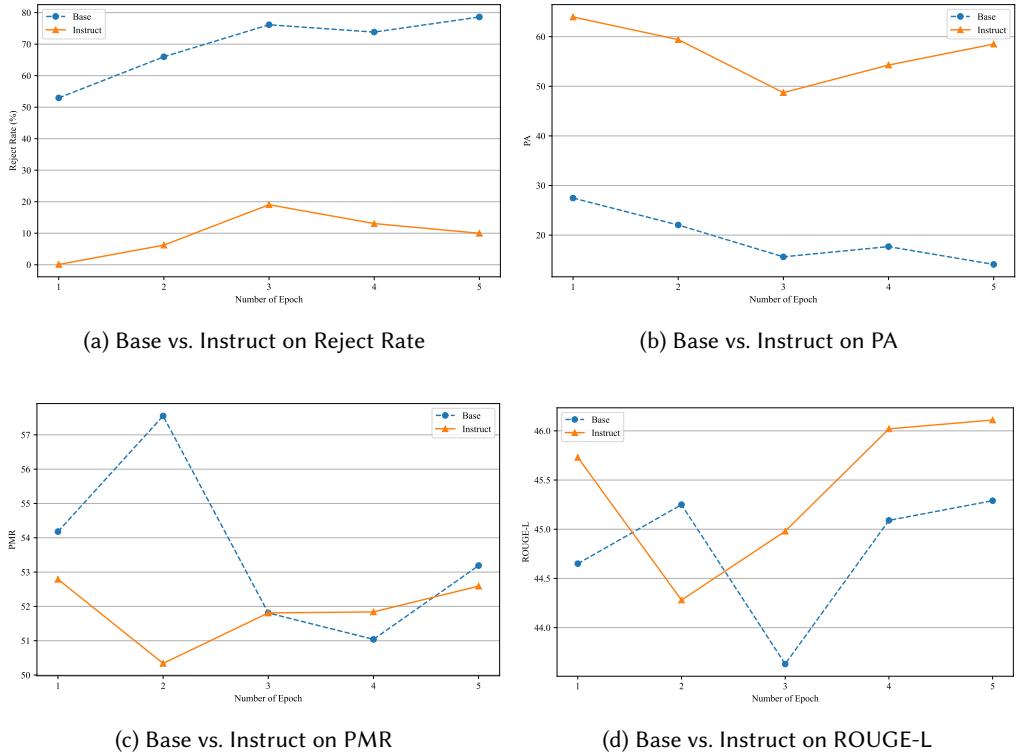


Fig. 5. Performance Comparison of Base and Instruct Mistral-7B Models Across Five Epochs.

evident from the first epoch and persist through the fifth, suggesting that the instruct model's pre-training for instruction-following enhances its ability to adapt to our logging task.

Findings 5: The instruct variant of SOLM model outperforms its base counterpart in automated logging statement generation, benefiting from its instruction-tuned foundation, which enhances task adherence and output quality.

In addition, the performance trends across epochs reveal that excessive fine-tuning can lead to diminishing returns. For both models, the Reject Rate and PA peak at the first epoch, where the Reject Rate is minimized, and the number of correctly predicted logging statement placements is maximized (Figure 5a and Figure 5b). Beyond the first epoch, both metrics show a slight decline or stabilization, with the Reject Rate marginally increasing and PA slightly decreasing by the fifth epoch. This trend suggests that additional fine-tuning may lead to overfitting, causing the models to become overly specialized to the training data and potentially losing some generalizability. For the instruct model, this could also imply a partial erosion of its pre-trained instruction-following robustness.

The venn diagram in Figure 4c further illustrates the overlap of corrected logging statement placements across epochs for the Mistral-7B-Instruct model. The central overlap (1120) indicates a stable core of corrections maintained across all five epochs, with the first epoch contributing the most unique corrected placements (40). The decline in unique contributions from later epochs (e.g.,

3 for the fifth epoch) supports the observation of diminishing returns and potential overfitting with prolonged fine-tuning.

Findings 6: Both base and instruct models achieve optimal performance at the first epoch for Reject Rate and PA, with prolonged fine-tuning leading to slight performance declines due to overfitting, indicating that excessive fine-tuning may compromise pre-trained capabilities.

4.3 RQ3: How effectively do SOLMs compare to existing methods and LLM baselines in automated logging statement generation?

Motivation. Having established optimal strategies for employing SOLMs in addressing the preceding RQs, this study aims to investigate the performance of SOLMs in automated logging statement generation compared to existing methods and the direct application of LLMs.

- (RQ3.1) How effectively do these methods determine appropriate logging locations?
- (RQ3.2) What is the quality of the logging statements generated by these methods?
- (RQ3.3) When evaluated by an LLM acting as a judge, how does the overall quality of the logging statements produced by these methods compare?

Approach. To address RQ3, we evaluate the performance of SOLMs in automated logging statement generation against existing method (i.e., LANCE, LEONID, Unilog, and Fastlog) and LLMs (i.e., Claude3.7sonnet, Deepseek-coder-v3, GPT4o, and LLAMA-405B). We assess the logging location accuracy (PA), the statement quality (LA, AOD, PMR, F1, BLEU-4, and ROUGE-L), and overall quality via our LLM judger. Target SOLMs (LLaMA-8B, Mistral-7B, CodeLlama-13B, Qwen2.5-coder-14B) are fine-tuned with LoRA and RAG, while LLMs were tested in base, ICL, RAG, and COT configurations. To ensure a comprehensive evaluation of SOLMs' capabilities, we select the largest parameter models available within the SOLM definition (i.e., open-source models with fewer than 14B parameters). This choice maximizes the potential performance of SOLMs, allowing us to showcase their optimal effectiveness in automated logging statement generation.

Result. (RQ3.1) Table 5 shows the performance comparison of automated logging statement generation approaches across all metrics. The table shows that Qwen2.5-coder-14B-RAG-LoRA achieves the highest PA at 66.20%, outperforming all other models, including LLMs like Claude3.7sonnet-RAG (65.90%) and Deepseek-coder-v3-RAG (65.20%), as well as existing methods like Fastlog (53.40%). Among SOLMs, Mistral-7B-RAG-LoRA (63.97%) and CodeLlama-13B-RAG-LoRA (63.57%) also surpass most LLMs and all existing methods, indicating that fine-tuning with LoRA and RAG significantly enhances the ability of SOLMs to identify appropriate logging locations compared to both traditional approaches and LLMs in various configurations.

(RQ3.2) For statement quality, Qwen2.5-coder-14B-RAG-LoRA again leads across all metrics. These results surpass the best-performing LLM, deepseek-coder-v3-RAG (e.g., 68.39% LA, 18.97% BLEU-4), and existing methods like Fastlog (e.g., 59.26% LA, 13.28% BLEU-4). CodeLlama-13B-RAG-LoRA also performs strongly, particularly in BLEU-4 (24.39%) and ROUGE-L (46.91%), closely rivaling Qwen2.5-coder-14B. The superior performance of fine-tuned SOLMs suggests that targeted optimization enables them to generate more accurate, relevant, and contextually appropriate logging statements than both unoptimized LLMs and traditional methods.

(RQ3.3) Figure 6 illustrates the score distribution for LLM judger evaluating the quality of logging statements from various methods. First, the bar chart indicates the number of cases receiving each score (0, 1, 2, 3) for different models. Qwen2.5-coder-14B stands out with the highest number of cases scoring 3, alongside the lowest number of cases scoring 0. This distribution suggests that Qwen2.5-coder-14B consistently generates logging statements of higher quality. Second, the trend line representing the average score highlights Qwen2.5-coder-14B achieving the highest

Table 5. Performance Comparison of Automated Logging Statement Generation Approaches Across All Metrics.

Model	Location		Level		Variable		Text	
	PA	LA	LOD	PMR	F1	BLEU-4	ROUGE-L	
Existing Approach								
LANCE	44.67	48.23	80.60	26.84	48.33	11.21	29.38	
LEONID	46.74	49.67	81.88	28.04	49.65	12.63	31.33	
Unilog	51.27	56.34	84.58	34.19	50.46	14.05	34.68	
Fastlog	53.40	59.26	85.23	38.22	51.24	13.28	32.54	
Large Language Model								
Claude3.7sonnet-base	47.02	66.22	87.83	46.25	55.14	17.32	39.85	
Claude3.7sonnet-ICL	62.80	62.46	86.64	44.70	55.06	14.93	36.84	
Claude3.7sonnet-RAG	65.90	65.89	88.01	45.78	56.49	17.39	39.64	
Claude3.7sonnet-COT	47.32	64.60	87.95	35.33	55.58	15.13	36.87	
Deepseek-coder-v3-base	53.65	67.85	88.04	48.23	55.14	17.42	38.40	
Deepseek-coder-v3-ICL	62.64	64.06	86.89	46.94	53.76	15.98	37.07	
Deepseek-coder-v3-RAG	65.20	68.39	88.08	49.28	55.93	18.97	41.32	
Deepseek-coder-v3-COT	49.05	65.11	87.31	34.96	56.12	14.31	35.32	
GPT4o-base	27.91	63.60	86.89	47.73	52.62	15.66	36.95	
GPT4o-ICL	52.45	56.44	84.63	44.51	52.96	13.02	32.56	
GPT4o-RAG	55.78	63.28	86.75	46.27	54.20	15.66	36.94	
GPT4o-COT	24.84	62.73	86.91	38.47	56.22	15.03	36.46	
LLAMA-405B-base	46.45	63.80	86.96	51.76	54.70	18.50	39.37	
LLAMA-405B-ICL	51.62	55.10	83.25	46.45	52.01	15.01	35.71	
LLAMA-405B-RAG	55.04	63.64	86.94	51.06	56.04	19.55	40.94	
LLAMA-405B-COT	15.25	60.92	85.23	39.74	50.94	18.22	37.71	
Fine-tuned Small Open-source Language Models								
LLAMA-8B-RAG-LoRA	56.84	63.56	87.37	50.15	58.22	19.37	42.03	
Mistral-7B-RAG-LoRA	63.97	69.50	88.64	52.79	57.89	20.62	41.70	
CodeLLAMA-13B-RAG-LoRA	63.57	64.43	87.17	53.90	58.59	24.39	46.91	
Qwen2.5-coder-14B-RAG-LoRA	66.20	69.92	89.36	54.53	59.93	24.05	46.51	

average score of 1.506, surpassing all other models, including Claude3.7sonnet-RAG (1.489) and Deepseek-coder-v3-RAG (1.467).

Findings 7: Fine-tuned SOLMs, particularly Qwen2.5-coder-14B, outperform both existing methods and LLMs across all evaluated metrics, demonstrating superior logging location accuracy and statement quality. The result of LLM judge further supports the high quality of SOLM-generated logging statements.

4.4 RQ4: Can SOLMs generalize logging statement generation across diverse code repositories?

Motivation. In real-world software development, logging practices vary significantly across projects due to differences in coding styles, project domains, and developer preferences. For SOLMs to be practically viable for automated logging statement generation, they must demonstrate robust generalization when applied to unseen repositories. Poor generalization could lead to ineffective

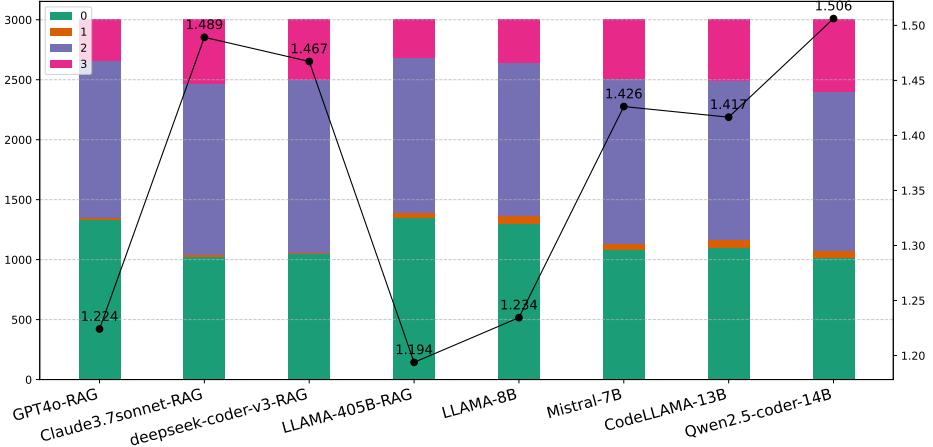


Fig. 6. Distribution of LLM Judger Scores for Generated Logging Statement Quality Across Models.

Table 6. Generalization Capabilities for SOLMs Across Diverse Code Repositories.

Train Data	Valid Data	Test Data	Model	PA	LA	AOD	PMR	F1	BLEU-4	ROUGE-L
R1, R3, R5, R7, R9	R2, R4, R6	R8, R10	Mistral	52.97	69.30	90.74	44.31	55.87	18.80	40.15
			Qwen2.5coder	55.54	71.67	91.86	44.67	57.20	20.21	42.22
R2, R4, R6, R8, R10	R1, R3, R5	R7, R9	Mistral	44.27	51.76	79.75	43.44	47.18	17.25	38.46
			Qwen2.5coder	50.71	56.19	81.96	45.71	53.30	18.48	40.50

logging statements that fail to capture critical runtime information or adhere to project-specific conventions, limiting the utility of SOLMs in cross-project settings.

Approach. To evaluate the cross-repository generalization ability of SOLMs, we design an experiment that trains models on a subset of repositories from the dataset and tests them on a distinct, non-overlapping set of repositories. We randomly partition the dataset into two groups, each containing five repositories, ensuring diversity in project domains. In each experimental run, we use one group of five repositories as the training set, three repositories from the other group as the validation set, and the remaining two repositories from the same group as the test set. The validation set primarily served to support RAG by providing a pool of examples from which the most similar code snippets are retrieved using the BM25 algorithm. This partitioning ensures that the test set represents unseen projects with potentially different coding styles and logging conventions, simulating real-world cross-repository scenarios. For this experiment, we select the two best-performing 7B SOLMs from RQ2.1: Mistral and Qwen2.5-coder. We fine-tune these models using the best-performing strategy identified in prior experiments, combining LoRA with RAG.

Results. Table 6 presents the performance of two fine-tuned SOLMs, Mistral-7B and Qwen2.5-coder-7B, in automated logging statement generation across diverse code repositories. The experimental setup involves training on a subset of repositories (R1, R3, R5, R7, R9), validating on another subset (R2, R4, R6), and testing on unseen repositories (R8, R10) in the first configuration, while the second configuration trains on Apache-dominated repositories (R1, R3, R5, R7, R9) and tests on non-Apache repositories. The results demonstrate the generalization capabilities of SOLMs and highlight the impact of similar logging practices on cross-project performance.

Result shows that both Mistral-7B and Qwen2.5-coder-7B exhibit robust performance. Specifically, Qwen2.5-coder achieves a PA of 55.54% and ROUGE-L of 42.22%, while Mistral-7B achieves comparable results with a PA of 52.97% and ROUGE-L of 40.15%. These metrics indicate that both models successfully generate accurate logging statements and identify appropriate logging locations in unseen repositories, even when the test set includes projects with distinct logging conventions. The high AOD (91.86% for Qwen2.5-coder) and ROUGE-L scores suggest that the generated logs closely align with ground-truth statements in terms of log level and text similarity. This reveals that SOLMs, when fine-tuned with LoRA and RAG, proficiently generalize across various project areas without experiencing a notable decline in performance.

Findings 8: SOLMs demonstrate strong generalization capabilities in automated logging statement generation, maintaining high performance across diverse, unseen repositories.

The performance difference between the two configurations in Table 6 highlights the influence of similar logging practices on cross-project generalization. In the first configuration, where both training and test sets include Apache open-source projects, the models achieve significantly higher performance (e.g., Qwen2.5-coder: PA 55.54%, ROUGE-L 42.22%) compared to the second configuration, where the training set comprises Apache projects, but the test set includes non-Apache projects (e.g., Qwen2.5-coder: PA 50.71%, ROUGE-L 40.50%). The performance drop in the second configuration (e.g., 4.83% lower PA and 1.72% lower ROUGE-L for Qwen2.5-coder) suggests that the absence of shared logging conventions, such as those prevalent in Apache projects (e.g., consistent verbosity levels and formatting styles), reduces the models' ability to generate contextually appropriate logs. Apache projects often adhere to standardized logging guidelines, which facilitate knowledge transfer during fine-tuning, whereas non-Apache projects may employ more varied or project-specific logging practices, posing challenges for generalization. This disparity underscores that similarity in logging practices between repositories can enhance cross-project performance.

Findings 9: Similar logging practices, such as those shared among Apache open-source projects, significantly improve the cross-project generalization of SOLMs.

5 Discussion

In this section, we provide a comprehensive analysis of our experimental results, exploring the strengths of using SOLMs in automated logging statement generation. Furthermore, we propose potential future research directions and discuss practical application scenarios to offer valuable insights for advancing this field.

5.1 Analysis of SOLMs' Advantages

5.1.1 Efficiency and Cost-Effectiveness. SOLMs exhibit remarkable efficiency and cost-effectiveness in automated logging statement generation, making them a compelling alternative to LLMs. Unlike LLMs, which often require extensive computational resources, including thousands of GPU hours for training and inference, SOLMs achieve comparable performance with significantly lower resource demands. For instance, our experiments demonstrate that the Qwen2.5-coder-14B model, with 14 billion parameters, can be fine-tuned within 6 hours using a single Nvidia A100 GPU, producing high-quality logging statements with a PA of 66.20% and a ROUGE-L score of 46.51% (Table 5). This efficiency reduces hardware costs and energy consumption, aligning with sustainable computing goals.

5.1.2 Privacy and Security. Privacy preservation is a standout advantage of SOLMs. Li et al. [35] highlight that LLMs often rely on cloud-based APIs, posing risks of proprietary code leakage. In contrast, SOLMs' smaller size enables local deployment, ensuring sensitive code remains secure. This is particularly valuable for companies where strict data protection is paramount, offering a safer alternative for logging generation.

5.1.3 Adaptability to Differnet Project. One of the key challenges in automated logging is adapting to enterprise-specific logging styles and conventions, which vary significantly across organizations due to differences in verbosity levels, error prioritization, or compliance-driven formatting. Our findings demonstrate that SOLMs, when fine-tuned with techniques such as LoRA and RAG, can effectively align with project-specific logging practices. This adaptability is particularly valuable in real-world scenarios where organizations maintain proprietary logging guidelines. Unlike general-purpose LLMs, which struggle to adapt without extensive retraining, SOLMs can be fine-tuned efficiently on internal codebases, ensuring alignment with organizational standards while minimizing computational overhead.

5.2 Future Work Directions

5.2.1 Integration into Development Tools. To maximize the practical impact of SOLMs in automated logging, future work should focus on integrating these models into widely used development tools, such as integrated development environments (IDEs), and CI/CD platforms. Real-time logging statement suggestions during code authoring or automated insertion during code reviews could streamline the development process and reduce manual effort. For instance, an IDE plugin leveraging a fine-tuned SOLM could analyze code context on-the-fly, recommend logging points, and suggest high-quality logging statements tailored to the project's conventions. Such integrations would require optimizing SOLMs for low-latency inference and ensuring compatibility with diverse development workflows. Additionally, incorporating user feedback mechanisms into these tools could enable iterative refinement of generated logs, further aligning them with developer preferences.

5.2.2 Addressing Dynamic Logging Requirements. Logging practices often evolve during a project's lifecycle due to changing requirements, such as new debugging needs or compliance regulations. SOLMs must be capable of adapting to these dynamic requirements without requiring extensive retraining. Future research could investigate continual learning techniques to enable SOLMs to incrementally adapt to new logging conventions or project-specific requirements. For instance, online fine-tuning approaches could allow SOLMs to learn from newly added logging statements in a repository, ensuring sustained alignment with evolving practices. Additionally, exploring active learning strategies, where SOLMs query developers for feedback on ambiguous logging scenarios, could further enhance their adaptability.

6 Threats to Validity

6.1 Internal Validity

Selection of hyperparameters for fine-tuning. A potential threat to internal validity lies in the selection of hyperparameters for fine-tuning the SOLMs (e.g., learning rate, batch size, prefix length for prefix tuning, rank for LoRA). The study utilized recommended hyperparameters from official sources due to their proven effectiveness. However, these hyperparameters may not be optimal for all models or datasets, potentially introducing bias in the performance results. Suboptimal hyperparameter choices could lead to underperformance or overfitting, affecting the observed effectiveness of SOLMs compared to baseline LLMs or existing methods. To mitigate this, we

conducted preliminary experiments to validate the chosen hyperparameters on a subset of the AL-Bench dataset, ensuring reasonable performance. Nonetheless, a more exhaustive hyperparameter search may further enhance model performance and reduce this threat. **The potential data leakage.** A potential threat to the internal validity of our study is the possibility that the AL-Bench dataset, which comprises logging statements from 10 widely used open-source projects, may have been included in the pre-training corpora of the SOLMs or LLMs evaluated. Since these models are pre-trained on large-scale datasets, often including publicly available code repositories from platforms like GitHub, there is a risk that some or all of the AL-Bench projects were part of their training data. Such data leakage could artificially inflate the performance of these models, particularly in zero-shot or few-shot settings, potentially skewing our results and conclusions. To mitigate this threat, we carefully analyzed the performance of base (non-fine-tuned) models in our experiments. The results, as shown in Table 3, indicate that base models, such as Qwen2.5-coder (PA: 4.30%), exhibit significantly lower performance compared to their fine-tuned counterparts (PA: 62.40%). This substantial performance gap suggests that the base models, despite potential exposure to AL-Bench data during pre-training, do not inherently possess the task-specific knowledge required for high-quality automated logging statement generation. Instead, the superior performance of fine-tuned SOLMs is primarily attributable to our fine-tuning strategies (e.g., LoRA and RAG), which adapt the models to the specific logging task and dataset. Thus, we argue that any potential data leakage has minimal impact on the validity of our conclusions, as the observed improvements stem from task-specific fine-tuning rather than pre-existing knowledge from pre-training. Nonetheless, to further address this threat in future work, we recommend evaluating models on proprietary or newly created datasets that are guaranteed to be absent from pre-training corpora.

6.2 External Validity

The representativeness of the dataset. A potential threat to generalizability is that the AL-Bench dataset, comprising 10 open-source projects, may not fully represent logging practices in proprietary codebases. We mitigated this by selecting projects from diverse domains (e.g., task scheduling, messaging systems, IoT platforms), ensuring broad coverage of logging requirements. However, similar to prior work [35], our dataset is predominantly Java-based, which may limit the generalizability of SOLM's performance in generating log statements for other programming languages. This language-specific focus could restrict insights into how SOLM performs across diverse language ecosystems, potentially affecting its applicability in non-Java contexts. **The selection of SOLM.** Another potential threat to the generalizability of our findings lies in the selection of specific SOLMs evaluated in this study. While these models were chosen based on their established performance in software engineering tasks, they may not fully represent the diversity of available SOLMs or future advancements in model architectures. For instance, other SOLMs with different pre-training datasets, architectural designs (e.g., transformer variants or mixture-of-experts models), or domain-specific optimizations might exhibit varying performance in automated logging statement generation. To mitigate this threat, we selected models with broad applicability in code-related tasks and ensured they were fine-tuned using techniques (e.g., LoRA and RAG) to align with logging-specific requirements. However, future work should explore a wider range of SOLMs, including those with different training corpora or specialized architectures, to validate the robustness of our findings across diverse model ecosystems.

6.3 Construct Validity

Adequacy of evaluation metrics for logging quality. A potential threat to construct validity lies in whether the chosen evaluation metrics fully capture the quality of generated logging statements. These metrics primarily assess syntactic similarity to ground-truth logs (e.g., ROUGE-L for text

similarity and correctness of logging location (PA). However, high-quality logging statements must also provide actionable insights for developers, such as facilitating debugging or system monitoring, which may not be fully reflected by these metrics. For instance, a generated log might score high on ROUGE-L due to textual similarity but fail to capture critical runtime context (e.g., omitting key variables or using an inappropriate verbosity level). To mitigate this, we incorporated the LLM-as-a-judge approach to assess overall quality holistically. Nevertheless, future work could include developer-centric evaluations, such as user studies, to validate the practical utility of generated logs. **Representativeness of the LLM judger result.** The use of an LLM to evaluate the quality of generated logging statements introduces a construct validity threat if the LLM’s judgments do not align with human developer preferences. While the LLM-as-a-judge approach has shown promise in software engineering tasks [64], its scoring may not fully capture nuanced aspects of log quality, such as clarity, relevance to specific debugging scenarios, or adherence to project-specific logging conventions. Misalignment between LLM and human judgments could lead to over- or underestimation of SOLM performance. Therefore, incorporating human evaluations or domain-specific rubrics in future work could enhance the alignment between the LLM judger and practical logging needs.

7 Related Work

7.1 Automated logging statement generation

Traditionally, the automation of logging statements is divided into two primary stages [4, 16]: the identification of logging locations and the creation of logging statements. These stages are respectively denoted as where to log and what to log [81]. In addressing the complexities associated with determining where to log, various methodologies have been investigated by researchers to identify appropriate logging locations within source code [24, 30, 37, 71, 74, 79, 83]. Regarding what to log, the generation of logging statements is usually segmented into three specific subtasks: the generation of logging text [8], the selection of logging variables [45, 76], and the prediction of the logging level [32, 38, 42, 49].

The latest methodology offers a solution for the automatic generation of logging statements, addressing the selection of logging locations, determining the levels of statements, composing content, and identifying variables in a single step. Mastropaolet al. [48] introduced LANCE, a pioneering comprehensive tool that creates complete logging statements powered by T5. In addition to this, they developed LEONID [47], which integrates deep learning with information retrieval techniques to enhance performance. Meanwhile, Xu et al. [68] presented UniLog, grounded in the in-context learning framework of LLMs. Additionally, Xie et al. [67] introduced FastLog, which is capable of swiftly generating and inserting entire logging statements. Furthermore, Li et al. [36] proposed SCLogger, noted as the first approach to generate contextualized logging statements utilizing inter-method static context.

In this paper, we distinguish our work by focusing on the use of SOLMs for automated logging statement generation, addressing the limitations of LLMs in terms of privacy, computational efficiency, and adaptability to enterprise-specific logging practices. Unlike prior proposed approaches, which predominantly rely on LLMs, our study leverages fine-tuned SOLMs. This enables local deployment, mitigating privacy risks associated with cloud-based LLM APIs, and significantly reduces computational overhead, aligning with sustainable computing goals. Furthermore, our comprehensive evaluation using the AL-Bench dataset [62] demonstrates SOLMs’ robust generalization across diverse, unseen repositories, a critical aspect not extensively explored in prior work. By systematically investigating prompting strategies and fine-tuning techniques, we provide a

scalable and practical solution for automated logging that balances performance with resource constraints, offering a viable alternative for real-world software development.

7.2 Studies in logging practices

Advancements in logging within software engineering have sparked a growing interest in exploring logging practices across various domains. Zeng et al. [77] and Chen[2] extended the work of Yuan et al. [75] by analyzing log statements in Android and Java systems, revealing the widespread occurrence of logging in these environments. Kabinna et al. [26] investigated how changes such as bug fixes, feature enhancements, and code refactoring often lead to revisions in logging statements. Lai et al. [28] provided insights into logging code constructs at both file-level and block-level, addressing nine key research questions focused on statistical and content analysis. Li et al. [31] conducted a detailed qualitative study of the advantages and challenges associated with logging in software development, while Zhou et al. [82] explored the connection between logging practices and data leaks in mobile applications. Zhao et al. [78] analyzed IDs within log statements, proposing a straightforward approach to inject IDs to reduce information loss and examining the extent of information gained through this technique. Li et al.[39] investigated the characteristics and practical importance of dynamic variables, proposing a variable-aware log abstraction technique. Li et al.[35] introduced a study on LLM-assisted logging statement generation, demonstrating that prompt-based zero-shot or few-shot learning significantly enhances the generalization capabilities of LLMs. Tan et al. [62] proposed AL-Bench, which is a comprehensive benchmark designed specifically for automatic logging tools.

8 Conclusion

In this paper, we address the challenges associated with manual logging statement generation by comprehensively investigating the potential of SOLMs as a more viable alternative to resource-intensive and privacy-concerning LLMs. We conduct an extensive, large-scale empirical study to systematically evaluate the efficacy of four prominent SOLMs. This evaluation encompasses various interaction strategies, such as RAG; PEFT techniques, with a focus on LoRA; the impact of different model sizes; and the comparative performance of base versus instruction-tuned model types.

Our key findings provide several critical insights into leveraging SOLMs for this task. We demonstrate that RAG significantly enhances the performance of SOLMs in generating logging statements, and LoRA proves to be a highly effective PEFT technique, enabling substantial improvements with minimal trainable parameters. While larger SOLMs generally yield better results, this is balanced by increased computational demands, highlighting an important performance-resource trade-off. Furthermore, instruction-tuned SOLMs consistently outperform their base counterparts, benefiting from their inherent instruction-following capabilities. Most notably, our research establishes that fine-tuned SOLMs, particularly Qwen2.5-coder-14B, can surpass existing specialized logging tools and even larger LLM baselines in both the accuracy of predicting logging locations and the quality of the generated statements. These findings are further corroborated by LLM-as-a-judge evaluations, which confirm the high quality of SOLM-generated outputs. Additionally, we find that SOLMs exhibit robust generalization capabilities across diverse, unseen code repositories, underscoring their practical applicability.

In conclusion, this study provides strong evidence that appropriately fine-tuned SOLMs offer a powerful, efficient, privacy-preserving, and adaptable solution for automated logging statement generation. By making our methodology, datasets, and results publicly available [54], we aim to stimulate further research and development in this domain, ultimately contributing to improved software maintenance practices.

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