# Resolving Crash Bugs via Large Language Models: An Empirical Study

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*Abstract*—Crash bugs cause unexpected program behaviors or even termination, requiring high-priority resolution. However, crash bugs are often associated with complicated root causes, including issues in the source code and external environmental factors (e.g., third-party library dependencies). Thus, manually resolving crash bugs is challenging and labor-intensive, and researchers have proposed various techniques for their automated localization and repair.

ChatGPT, a recent large language model (LLM), has garnered significant attention due to its exceptional performance across various domains. This work performs the first investigation into ChatGPT's capability in resolve real-world crash bugs, focusing on its effectiveness in both localizing and repairing code-related and environment-related crash bugs. Specifically, we initially assess ChatGPT's fundamental ability to resolve crash bugs with basic prompts in a single iteration. We observe that ChatGPT performs better at resolving code-related crash bugs compared to environment-related ones, and its primary challenge in resolution lies in inaccurate localization. Additionally, we explore ChatGPT's potential with various advanced prompts. Employing role-play prompts effectively enhances resolution capabilities, while continuous interaction aids ChatGPT in acquiring relevant knowledge, improving overall effectiveness. Furthermore, by stimulating ChatGPT's self-planning, it methodically investigates each potential crash-causing environmental factor through proactive inquiry, ultimately identifying the root cause of the crash. Based on our findings, we propose IntDiagSolver, an interaction methodology designed to facilitate precise crash bug resolution through continuous interaction with LLMs like ChatGPT. Evaluating IntDiagSolver on multiple LLMs reveals consistent enhancement in the accuracy of crash bug resolution, including ChatGPT, Claude, and CodeLlama.

# I. INTRODUCTION

Crash bugs are often considered critical issues as they might cause unexpected program termination and disrupt normal user operations [1], [2]. Resolving crash bugs can be timeconsuming and labor-intensive, since crash bugs often have various causes, including both code issues (*e.g.*, bugs in the source code) and environment issues (*e.g.*, improper operating system versions, hardware configurations, or third-party library dependencies) [3]. In particular, for the crash bugs caused by buggy code (*i.e.*, code-related crash bugs), many efforts have been dedicated to automatically localizing [4], [5], [6] and repairing [7], [8], [9] them; for the crash bugs caused by environment issues (*i.e.*, environment-related crash bugs), due to the large space of potential causes, existing techniques mainly rely on adopting similar solutions from online Q&A forums such as Stack Overflow (SO) [3], [10], [11]. However, these approaches exhibit limited generalizability, failing to resolve crash bugs not previously discussed in online Q&A forums.

ChatGPT [12], a recent large language model (LLM) developed by OpenAI, has shown remarkable capabilities in various domains, including mathematics [13], [14], education [15], [16], and natural language processing [17], [18]. In particular, due to being pre-trained on text and code corpora, ChatGPT has also shown promising effectiveness in software engineering tasks, such as software comprehension [19], [20] and code generation [21], [22], [23]. Therefore, there have emerged some preliminary work that investigates the capability of ChatGPT in bug fixing. For example, Dominik et al.[24] compare the capability between ChatGPT and existing learning-based techniques on fixing code-related bugs; Xia et al.[9] incorporate the conversational capability of ChatGPT by leveraging ChatGPT to fix code-related bugs in multiple rounds. Although these studies show the promising potential of ChatGPT in bug fixing, their evaluation still focuses on a rather simple scenario. First, both of them only consider code-related crash bugs (e.g., primarily simple algorithmic bugs from toy programs in QuixBugs [25]), leaving it unclear how ChatGPT performs on resolving environment-related crash bugs in realworld software; Second, they either provide ChatGPT with the ground-truth buggy location or a small scope of potentiallybuggy code, which have not fully explored ChatGPT's fault localization capability for crash bugs; Third, they mainly interact with ChatGPT via a fixed small set of prompts, leaving it unexplored how different prompts under different interaction strategies effect ChatGPT's capability of resolving crash bugs.

To fill these knowledge gaps, we first perform a comprehensive study to investigate ChatGPT's capability in resolving real-world crash bugs by exploring how effective ChatGPT is in *localizing* and *repairing* both *code-related* and *environmentrelated* crash bugs with a diverse set of prompts. In particular, we explore the crash-bug-resolving capability of ChatGPT with (i) basic prompts that only include naive instructions in one-round interaction, and (ii) advanced prompts that incorporate different prompt templates and multi-round prompts. We answer the following two research questions, respectively.

• **RQ1 (Basic Prompts)**: How effective is ChatGPT in locating and repairing code-related and environment-related crash bugs with the basic prompt?

- **RQ2** (Advanced Prompts): How can advanced prompts improve ChatGPT's capability of resolving crash bugs?
- RQ2.a (Prompt Templates): How do different prompt templates effect ChatGPT's capability of resolving crash bugs?
- RQ2.b (Multi-round Prompts): How do multi-round prompts effect ChatGPT's capability of resolving crash bugs?

According to our results on 100 real-world crash bugs (*i.e.*, 50 code-related and 50 environment-related crash bugs), we have the following main findings. First, we find that ChatGPT has better proficiency in resolving *code-related crash bugs* than *environment-related crash bugs*; second, we find that fault localization rather than repair is the bottleneck when ChatGPT resolves crash bugs. Third, we find that the efficacy of continuous interaction with ChatGPT facilitates the acquisition of relevant knowledge, thereby enhancing its resolution effectiveness. Additionally, we find the role-play prompts are critical, as they not only improve resolution outcomes but also stimulate ChatGPT's proactive questioning ability for self-planning. This enables ChatGPT to effectively guide the resolution process via step-by-step localization.

Based on our findings, we further propose a methodology IntDiagSolver to guide the interaction with LLMs for more accurate crash bug resolution. We propose distinct prompt templates emphasizing varying components of crash contexts for code-related and environment-related crash bugs respectively, along with different multi-round interaction strategies. Furthermore, we devise a strategy enabling LLMs to guide the repair process, proving beneficial for beginners with limited crash bug knowledge. We then evaluate our proposed methodology on a small dataset of 41 crash bugs by answering the following research question.

- **RQ3** (Evaluation of IntDiagSolver): How well does IntDiagSolver perform in resolving crash bugs?
- RQ3.a (Effectiveness of IntDiagSolver): To what extent can IntDiagSolver effectively resolve crash bugs?
- RQ3.b (Generalizability of IntDiagSolver): To what extent can the effectiveness of IntDiagSolver in crash bug resolution be generalized across different LLMs?

The results show that IntDiagSolver consistently improves the accuracy of resolving both code-related and environmentrelated crash bugs for four recent LLMs, with substantial enhancements ranging from 13.5% to 133.0% in localization and 17.1% to 258.8% in repair. Notably, there's an impressive improvement from 0/30 to 16/30 in the number of successfully repaired environment-related crash bugs on ChatGPT. These findings provide valuable insights and practical guidelines for future work.

The contributions of this work are summarized as follows:

- *The first empirical study* extensively examines ChatGPT's ability in localizing and repairing crash bugs, including both code-related and unexplored environment-related ones.
- Extensive findings and insights that reveal ChatGPT-based

crash bug resolution limitations, strengths, and the impact of various prompt designs.

• The first methodology IntDiagSolver that guides the interaction with LLMs for more effective crash bug resolution.

# II. STUDY SETUP

In this section, we introduce the benchmark and LLM selection/configuration used in our study.

#### A. Benchmark

Previous research [9], [26], [27] investigating the potential of LLMs in bug resolution commonly uses QuixBugs [28] as the benchmark dataset. However, this dataset has limitations: (i) it exclusively targets crash bugs that originate from buggy source code, neglecting those arising from environmental issues, which are prevalent and sometimes more challenging for developers [29], [30]; (ii) the dataset contains only 40 bugs in relatively simple scenarios, such as basic algorithm programs, failing to capture the complexity of real-world crash bugs. While other bug repair datasets like Defects4j [31], ManySStuBs4J [32], and UnifiedBugDataset [33] exist, they all focus on code-related bugs.

To assess ChatGPT's effectiveness in resolving crash bugs comprehensively, we extend our analysis to include both coderelated and environment-related issues. Using SO threads, we create a benchmark with diverse real-world crash bugs, leveraging SO's alignment with real-world crash bugs and its rich contextual information on buggy code's purposes and dependencies.

Establishing Data Pool. Following prior research [2], [3], we focus on crash bugs in the Java program due to their prevalence [10]. To construct our benchmark, we select highquality threads from the SO data dumps [34] based on the following inclusion criteria: (1) Thread titles or tags containing the keyword "Java", (2) Thread titles or tags containing the keywords "exception" or "error", (3) Threads with an accepted answer, (4) Threads with at least one positive vote for their question, (5) Threads with concrete error symptoms (i.e., code or stack trace) to ensure sufficient context for understanding the crash bug, and (6) Threads containing at least one common Java exception type (e.g., NullPointerException). Furthermore, to collect a comprehensive list of common Java exception types for Criterion-6, we systematically parse 35,773 Java libraries from Maven Central [35] based on the Libraries.io dataset [36] and JDK 1.8 [37]. In addition, given that most LLMs only support limited length of textual inputs, we further include two exclusion criteria. (7) Filtering out threads with overlong questions given the limited input length taken by ChatGPT (*i.e.*, 1,000 tokens). (8) Filtering out threads with image content. In this way, we collect 67,248 SO threads related to crash bugs as the pool.

**High-Quality Sample Selection.** To ensure the benchmark's representativeness while minimizing human effort, we randomly sampled 100 threads from this pool. Two authors independently assessed each thread using predefined criteria. Only threads consistently rated as high quality by both assessors were included in the final benchmark and the accepted answers in the threads were considered as the ground truth solutions to the corresponding crash bugs. Note that threads are considered low quality if they only offer vague answers (*e.g.*, troubleshooting tips or general fixing directions) without detailed solutions. Considering our study covers both coderelated and environment-related crash bugs, we continued sampling and assessment until we had 50 qualified SO threads for each type, *i.e.*, 100 crash bugs in total.

# B. LLM Configuration

In our study, we primarily utilized ChatGPT, a notable exemplar in LLM advancements, for our first part experiments (RQ1 and RQ2). We opted for the gpt-3.5-turbo model. This choice, over GPT-4, was driven by its more rapid response and cost-effectiveness [38].

# III. RQ1: BASIC PROMPTS

In this RQ, we study ChatGPT's capability in localizing and repairing code-related and environment-related crash bugs with the basic prompt on our constructed benchmark.

#### A. Resolving Code-related Crash Bugs



(a) Code-related Crash Bug (b) Environment-related Crash Bug Figure 1. Examples of Crash Bugs

1) Basic Concepts: Code-related crashes result from errors in the program's code implementation and are not environment-related. Figure 1(a) provides an example of a code-related crash bug with its crash description (**Cra-Des**). The description typically consists of three parts: buggy code, crash information, and crash context.

- **Buggy Code** (**B-Code**) : This snippet of code triggers the crash and often contains syntax or semantic errors that lead to unexpected program behaviour.
- **Crash Information (Cra-Info)** : This segment includes the exception type, error message, and crash trace. Exception type denotes the nature of the error, *e.g.*, divide-by-zero. The error message provides a human-readable description of the error. The crash trace offers a stack trace of the program execution at the time of the crash, assisting in locating the error.
- Crash Context (Cra-Cont) : This section describes the broader crash context, including symptoms, potential

causes, relevant inputs, the buggy code's purpose, configurations, or dependencies possibly contributing to the error. Such details are crucial for replicating the crash and grasping its underlying cause.

These three parts offer varying levels of detail for a crash bug, with a specific progression. The buggy code offers pinpoints the code segment responsible for the crash, essential for identifying the root cause of the bug. The crash information aids in pinpointing the bug's location and reason. The crash context provides a natural language description of the bug, offering a higher-level view to comprehend the bug's behavior and potential causes.

2) Design: We assessed ChatGPT's ability to localize and repair 50 code-related crash bugs in our benchmark.

**Prompt Design.** A series of prompt templates (Basic-Prompt-1 to Basic-Prompt-4) were designed for interacting with Chat-GPT, covering different levels of granularity of information.

**Basic-Prompt-1:** This is my code: [B-CODE] I'm getting an exception, how do I fix it?

- **Basic-Prompt-2:** This is my code: [B-CODE] I'm getting [CRA-INFO], how do I fix it?
- **Basic-Prompt-3:** [CRA-CONT] This is my code: [B-CODE] I'm getting [CRA-INFO], how do I fix it?

**Basic-Prompt-4:** [CRA-DES] This is my error lines: [LOC] how to fix it?

**Interaction Procedure.** For each code-related crash bug in our benchmark, we divided its description into three parts and engaged ChatGPT using specific prompts, providing information progressively. Initially, we used Basic-Prompt-1, containing only the buggy code. If this didn't yield an accurate repair, we attempted Basic-Prompt-2, which included additional crash information. If the bug remained unresolved, we used Basic-Prompt-3, providing crash context. If the crash bug persisted without a correct resolution, we employed Basic-Prompt-4, pinpointing the specific *localization in the buggy code lines (LOC)*, meaning the actual lines of code needing modification. This simplified the task for ChatGPT, focusing solely on repairing the crash bug without localization, allowing us to explore the model's repair capabilities.

We recorded and analyzed ChatGPT's responses to each prompt, compared them with the corresponding ground truth solution, and assessed the correctness of localization and repair (see Section III-A3). The judgments were made independently by two authors. If the judgments were different, a third author was assigned to make an additional judgment. The final annotation results were determined based on the majority principle. As a result, the kappa coefficient [39] for localization and repair were 0.89 and 0.92 respectively, indicating almost perfect agreement.

**Reliability Assurance.** To ensure the reliability of our experiments, we implemented several precautions. Firstly, we initiated a new session with ChatGPT for each interaction to avoid potential bias from prior conversations. Additionally, we conducted experiments on multiple accounts using different machines to minimize the impact of environmental variables. Considering the non-deterministic nature of ChatGPT, fur-

thermore, we conducted experiments where two independent evaluators simultaneously interacted with ChatGPT to obtain the responses for each prompt. Subsequently, we assessed both evaluators' responses and compared their conclusions regarding localization and repair correctness. In cases of disagreement, a third evaluation was performed using the same prompt to determine the accuracy of the response, following a majority-based decision-making process. It's worth noting that only a small percentage of queries (6%, 3 out of 50) required this third evaluation to reach a consensus.

3) Metrics: For each prompt, we conducted a manual examination of ChatGPT's responses and performed separate qualitative analyses to assess its localization and repair capabilities. In the localization evaluation, a ChatGPT's response was deemed correct if the line of code it identified for modification matched the faulty code line identified in the benchmark. In the repair evaluation, ChatGPT was required to provide an accurate code patch that matched the one in the benchmark to be considered correct. To enhance the clarity of localization accuracy, we also recorded the number of solutions ChatGPT provided for each crash bug, calculating the accuracy rate as the ratio of correct to total solutions given. Additionally, we logged the code length of each crash bug to examine its influence on ChatGPT's localization and repair capabilities.

4) Results: We collected the responses of ChatGPT for different prompts and manually analyzed the contents of the responses. For code-related crash bugs, ChatGPT's responses can encompass several aspects, such as confirming code functionality, explaining error messages, identifying potential causes, offering textual fixes, presenting repaired code, discussing alternatives, and providing warnings. However, not all responses address every aspect, and alternative reasons and solutions may not always be explored.

Table I illustrates the experimental results of ChatGPT's ability to resolve code-related crash bugs. The analysis from different aspects yields the following main conclusions (Finding 1-4).

**Overall Resolution Capability.** The experimental results presented in Table I indicate that ChatGPT has significant potential in fixing code-related crash bugs. Specifically, when provided with full crash description information, ChatGPT was able to correctly localize 42 out of 50 crash bugs (84.0%), and repaired 38 of them (76.0%). Furthermore, ChatGPT provided a unique and clear answer for the majority of repaired crash bugs, with only 7.9% (3 out of 38) repaired crash bugs providing multiple possible solutions.

**Finding 1**: ChatGPT excels in resolving code-related crash bugs, displaying proficiency in both bug localization and repair.

**Contextual Information Impact.** Firstly, ChatGPT has the ability to resolve code-related bugs using only the information in the buggy code. In Table I, ChatGPT was able to correctly localize and repair 40% (20 out of 50) of crash bugs when given only the buggy code with Basic-Prompt-1. This shows

that the buggy code is essential for ChatGPT to resolve code-related bugs.

Furthermore, Table I shows that providing more effective crash description information significantly increased Chat-GPT's ability to localize and repair crash bugs. It's important to note that the number of localized and repaired crash bugs increased simultaneously, **indicating that effective crash description helped ChatGPT improve its bug localization accuracy**.

The pivotal role of exception type and error message in crash localization is highlighted by the responses of ChatGPT and the analysis of two specific cases: crash bugs 68199510 [40] and 65084069 [41] (the SO thread IDs of the crash bugs). In both cases, ChatGPT provided environment-specific solutions, leading to misresolving. This is because the exception types *NoClassDefFoundError* and *NoSuchMethodError* are commonly associated with environmental issues.

Additionally, the complete stack trace in code-related crash bugs is relatively less important. To validate this hypothesis, additional trials were conducted on specific posts. in the case of crash bug 22928450[42], When furnished solely with the buggy code, crash context, and exception type, ChatGPT generated the correct repair solution. However, substituting the exception type information with a stack trace lacking exception type led to ChatGPT's inability to accurately localize this crash bug. Therefore, to improve the repair effectiveness, **the exception type information should be explicitly emphasized using natural language when providing crash description information.** 

Crash context can also improve ChatGPT's localization capabilities, including the purpose of the program, the symptoms including when the crash occurred (*e.g.*, which function was invoked, or which application segment failed to produce the correct output), when the program run normally, and the user's own testing information and ineffective attempts to fix the issue.

**Finding 2**: Providing more effective crash description information significantly improves ChatGPT's ability to localize code-related bugs. Exception type and error message are crucial for precise location, and additional context in natural language descriptions can further enhance its performance.

**Localization vs. Repair.** Among the queries with full description, there are only 7.1% (3 of 42) that can be correctly localized but cannot be accurately repaired. In addition, four out of the seven initially unlocatable crash bugs are successfully repaired after providing the real buggy code line to ChatGPT. These results indicate that ChatGPT's resolving bottleneck mainly lies in localization. If it can accurately localize the crash bugs, it can successfully repair the vast majority of them. From the results shown in Table I, only 8.0% (4 of 50) crash bugs could not be repaired despite being able to localize the fault line.

Experimental Results on ChatGPT's Crash Bug Resolution. The "Information" column contains input data, while "Localization" and "Repair" columns show the number of successfully localized and repaired crash bugs. "Loc. with Multi." indicates cases where ChatGPT localized the bug but offered multiple solutions, and "Code ¿50 Lines" shows the count of bugs with code exceeding 50 lines.

| Туре         | Prompt         | Information                           | Localization      | Repair   | Loc. with<br>Multi. | Code<br>>50<br>Lines | Accuracy        |
|--------------|----------------|---------------------------------------|-------------------|----------|---------------------|----------------------|-----------------|
| Code related | Basic-Prompt-1 | B-Code                                | 20                | 20       | 2                   | 2                    | 0.395           |
|              | Basic-Prompt-2 | B-Code + Cra-Info                     | 30 ( <b>+10</b> ) | 28 (+8)  | 2                   | 6                    | 0.595 (+50.6%)  |
|              | Basic-Prompt-3 | B-Code + Cra-Info +<br>Cra-Cont       | 42 (+22)          | 39 (+19) | 3                   | 10                   | 0.825 (+108.9%) |
|              | Basic-Prompt-4 | B-Code + Cra-Info +<br>Cra-Cont + LOC | 46 (+26)          | 43 (+23) | 3                   | 13                   | 0.905 (+129.1)  |
| Env. related | Basic-Prompt-2 | B-Code + Cra-Info                     | 7                 | 5        | 5                   | /                    | 0.063           |
|              | Basic Prompt 3 | B-Code + Cra-Info +<br>Cra-Cont       | 32 (+25)          | 20 (+15) | 21                  | /                    | 0.341 (+441.3%) |

Finding 3: The primary bottleneck in resolving coderelated crash bugs lies in localization rather than repair.

**Code Length Impact.** As shown in Table I, among the crash bugs with complex buggy code (exceeding 50 lines), only 2 of 13 (15.3%) can be correctly localized with only buggy code provided. However, the inclusion of crash information and crash context enables successful localization of an additional 4 crash bugs, respectively. Out of the 4 crash bugs that require the buggy lines using Basic-Prompt-4 to be localized and fixed, 3 contain code exceeding 50 lines.

**Finding 4**: Longer code leads to a poorer localization ability, necessitating additional crash description information for effective localization.

# B. Resolving Environment-related Crash Bugs

1) Design: Figure 1(b) shows an example of environmentrelated crash bug from our benchmark. Similar to our setup for code-related crash bugs (see Section III-A2), we also investigate ChatGPT's ability for environment-related crash bugs at different levels of granularity. However, as not every environmental crash description includes a code snippet, and the root cause of the environment-related crash bugs unrelated to the code implementation itself, we differentiate environmental crashes solely based on natural language descriptions and non-natural language information (i.e., code snippets and crash information). For each environment-related crash bug, we initially present only the non-natural language information and employ the Basic-Prompt-2 to evaluate ChatGPT's performance. If an accurate repair cannot be achieved, we provide the full information for a subsequent attempt using Basic-Prompt-3.

2) Metrics: We evaluated ChatGPT's ability to localize and repair for each crash bug through manual assessment. In the localization evaluation, we recognized the ChatGPT's localization as correct if it identified the correct cause of the exception (*e.g.*, a library version problem or a missing dependency problem). In the repair evaluation, a specific repair plan was required (*e.g.*, upgrading or downgrading to a specific library version). Additionally, the number of crash bugs that have been correctly localized with multiple solutions provided, as well as the precision of ChatGPT's answers will also be recorded. The arbitration method employed for evaluation is consistent with the experimental setup in coderelated crash bugs, the kappa coefficient for location and repair in environment-related crash bugs were both 0.97, indicating almost perfect agreement.

*3) Results:* ChatGPT exhibits diminished proficiency in environment related crash bugs resolution than code-related crash bugs, as evidenced by the lower localization and repair accuracy and more candidate solutions provided, indicating an inherent uncertainty in ChatGPT's bug localization.

Based on the results presented in Table I and our detailed analysis of specific examples, we can draw several conclusions (Finding 5-8) from different aspects.

**Overall Resolution Capability.** Table I shows that ChatGPT can successfully identify 42 code-related crash bugs and 32 environment-related crash bugs with full crash description. Moreover, among the accurately localized responses, 21 out of 32 (65.6%) cannot provide a single clear solution. In some cases (e.g. crash bug 28097042 [43] and 24305296 [44]), Chat-GPT gives five or more possible solutions for the same crash bug, resulting in a low hit rate. Different form code-related crash bugs, full stack trace is more crucial for environment-related crash bugs diagnosis, as which contains a great deal of environment-related information.

**Finding 5**: ChatGPT shows lower proficiency in resolving environment-related crash bugs compared to code-related ones due to its inability to pinpoint the root cause, resulting in multiple imprecise candidate solutions.

**Localization vs. Repair.** Differing from the observations made while resolving code-related crash bugs, 10 instances with full crash descriptions were successfully localized but remained unrepaired (only 3 instences in resolving code-related crash bugs). This is due to ChatGPT's inclination to only identify potential root causes of environment-related crash bugs( such as a permission, version, or IP address problem), rather than offering specific repair steps in solutions when multiple solutions are provided. Thus, guiding ChatGPT to

Table I

provide explicit repair strategies is a challenge to be addressed in further explorations.

Finding 6: ChatGPT lacks specificity in providing solutions for environment-related crash bugs.

Contextual Information Impact. Table I shows that providing buggy code and crash information successfully identify 60% (30 of 50) of code-related crash bugs. Adding crash context only results in the successful location of 12 more bugs. Addressing environment-related crash bugs through buggy code and crash information identifies only 14% (7 of 50) of such bugs, with only 10% (5 of 50) successfully repaired. However, inclusion of crash context significantly increases success rates to 64% (32 of 50) for localization and 40% (20 of 50) for fixing environment-related crash bugs. This highlights the importance of crash context for environment-related crash bugs repair, compared to code-related crash bugs. However, leveraging ChatGPT to resolve environment-related crash bugs is challenging due to the subjective nature of crash context and its dependence on natural language, thereby placing higher demands on the questioner's proficiency.

**Finding 7**: In contrast to code-related crash bugs, the repair for environment-related crash bugs relies heavily on crash context.

We also observe that ChatGPT is unable to reason and localize the causes of a bug when the relevant environmental information is not included in the crash description. For instance, in the case of crash bug 49871007 [45], the exception description and stack trace only mentioned Resteasy 3.1.4.Final. However, the actual library version that needed modification was javax.ws.rs-api, while Resteasy 3.1.4.Final is an implementation of the JAX-RS-API 2.1 specification. In such cases, ChatGPT cannot effectively reason and localize the cause.

**Finding 8**: ChatGPT is unable to reason and localize the causes of crash bugs when the relevant environmental information is not included in the crash description.

Considering the high frequency and impact of version problems in environment-related crash bugs, which represent a significant proportion (19 out of 50 in our benchmark), we conducted a specialized analysis of these issues. We observed that ChatGPT typically recommends upgrading to the latest version to fix library version-related crash bugs, *e.g.*, bug 24305296 [44]. However, for cases where upgrading or downgrading to a specific version of the library was the solution (*e.g.*, bugs 43320334 [46] and 37771758 [47]), ChatGPT couldn't provide the right version number.

Finding 9: ChatGPT typically recommends upgrading to the latest version to solve library version-related issues.

# IV. RQ2: ADVANCED PROMPTS

In this section, we delve into the exploration of advanced prompts as a means to enhance ChatGPT's proficiency in addressing crash bugs. It's worth noting that our focus here primarily centers on crash bugs related to the environment. This emphasis on environment-related crash bugs arises from the findings in RQ1, which already demonstrated ChatGPT's strong performance in resolving code-related crash bugs, even with the basic prompt.

To achieve our objectives, we conduct experiments that investigate two key aspects of advanced prompts: prompt templates and multi-round prompts. Specifically, we aim to improve the design of prompt templates for single-round interactions (as detailed in Section IV-C), and we also seek to enhance the resolution performance by facilitating continuous interactions in multi-round scenarios (as discussed in Section IV-D and IV-E). Furthermore, we intend to underscore the effects and significance of our interaction approach by by offering a thorough analysis of a user study involving 10 distinct cases. The specific details of the 10 cases are provided in Section IV-A, while the evaluation metrics are explained in Section IV-B.

# A. Study Cases

To enhance ChatGPT's interaction with environment-related crash bugs, we selected 10 diverse cases that remained unrepaired despite complete crash descriptions provided in RQ1. These cases include dependency version issues, configuration settings problems, network issues, and user authority issues. Detailed information for each case is presented in Table II. These 10 cases will be used for specific experiments and analysis concerning each sub-problem.

 Table II

 SUMMARY OF CRASH BUGS USED AS CASE STUDIES

| Bug ID   | Crash Bug<br>Issue  | Solution Summary  |  |  |  |
|--|---|---|--|--|--|
| 30322026   | version issues  | replace smack-java with smack-android   |  |  |  |
| 51370703   | version issues  | downgrade the version of SLF4J from<br>1.8.0 to 1.7.X   |  |  |  |
| 37771758   | version issues  | downgrade the version of Glassfish server<br>from 4.1.1 to 4.1.0                              |  |  |  |
| 60210757   | version issues  | upgrade the version of to<br>mongo-kafka-connect later than 1.0.0                             |  |  |  |
| 49871007   | version issues  | upgrade the JAX-RS-API to 2.1   |  |  |  |
| 30559542   | version issues  | run Java program under a 32-bit JVM or<br>install the 64-bit version                          |  |  |  |
| 43320334   | version issues  | upgrade Chrome, Chrome driver and<br>Selenium   |  |  |  |
| 48637658   | network issues  | replace the local IP address with the<br>corresponding IP address for the Android<br>emulator |  |  |  |
| 67044715   | authority issues  | make sure the user has access to the table  |  |  |  |
| 42933291   | v33291         configuration<br>settings issues         install one of the normal arphic fo<br>the texlive variant. |   |  |  |  |
| 39858254 configuration add the TrustStore configuration settings issues server.xml |   |   |  |  |  |

# B. Metrics

We enlisted two participants with a minimum of three years of programming experience to assess ChatGPT's responses in our experiments. They first evaluated localization and repair accuracy, as in RQ1. To mitigate the influence of ChatGPT's inherent randomness, we conducted three trials for each case. Therefore, the accuracy metric was calculated based on the proportion of successful localizations and repairs across all 30 trials. Additionally, they rated the answers for usefulness, conciseness, and interactivity using a 4-point Likert scale [48] (1-disagree; 2-somewhat disagree; 3-somewhat agree; 4-agree) based on predefined statements (see the following). For each query, all scoring results were jointly determined by two participants through discussions.

- Usefulness: ChatGPT can provide useful solutions to help participants resolve crash bugs, including a detailed explanation of the root cause of the issue and a comprehensive solution.
- **Conciseness**: ChatGPT can provide clear and accurate solutions without redundant information.
- **Interactivity**: The conversation flows well across multiple rounds, without losing sight of previous context.

## C. RQ2.a: Prompt Templates

The quality of the prompt design directly affects the accuracy and effectiveness of LLMs' output. Previous research has demonstrated that prompt templates have a significant impact on ChatGPT's responses [49]. Therefore, we need to further explore how to improve prompt template design to enhance ChatGPT's performance in repairing environmentrelated crash bugs. This section focuses on how to design high-quality prompt templates and introduces corresponding experimental designs and results.

1) Design: Building on our experimentation experience and drawing inspiration from [50], we have crafted three distinct prompt templates for environment-related crash bugs.

**Multi-Solution-Prompt**: Please show me all potential solutions.

**Role-Play-Prompt**: I want you to act as a fault localization and program repair expert. You will be able to provide detailed solutions to fix the given program crash.

Chain-of-Thought-Prompt: Pleas fix it step by step.

Firstly, we explore whether ChatGPT can produce the correct solution that were previously unattainable, by promoting the generation of all possible solutions through the utilization of Multi-Solution-Prompt.

Drawing inspirations from [51], [52], [53], we identified that the implementation of role-play prompts and chain-of-thought prompt can significantly enhance ChatGPT's efficacy in localization and repair. Concatenating the above prompt with **Basic-Prompt-3**, we used these prompts to conduct comparative experiments on 10 studied cases. To mitigate any potential concerns with the randomness of ChatGPT's , we run three independent requests for each query and evaluated the answers using metrics.

2) *Results:* The experimental results of various prompt templates are presented in Table III. Compared to the basic prompt, the Multi-Solution-Prompt allows ChatGPT to offer more solutions, enhancing the likelihood of finding the correct one, but leading to decreased conciseness. The Chain-of-Thought-Prompt faces similar issues, introducing substantial redundant information and resulting in a low conciseness score of 0.2, rather than aiding ChatGPT in obtaining a more

accurate end-to-end solution. Compared to the Multi-Solution and Chain-of-Thought Prompts, which enhance localization and repair effectiveness but sacrifice conciseness, the Role-Play-Prompt excels in single-round interactions. It outperforms the basic prompt with 0.23 higher accuracy in repairs, a 1.23 higher usefulness score, and improved conciseness.

Furthermore, ChatGPT's ability to identify the root cause of the crash bugs improved. For instance, while the first two prompts also mentioned issues with Smack version in crash bug 30322026, they did not identify the incompatibility between Smack version and Android project as the root cause, while ChatGPT's responses with Role-Play-Prompt did. Therefore, we draw the following conclusion:

**Finding 10**: Role-play prompts significantly improve Chat-GPT's ability to localize and repair crash bugs.

## D. RQ2.b: Multi-round Prompts

We explored multi-round interactions to enhance ChatGPT's crash bug localization and repair abilities. Our hypothesis was that continuous interactions between users and ChatGPT could yield more precise responses, ultimately improving performance.

1) Design: To test our hypothesis, we designed experiments to test the effectiveness of providing feedback on ChatGPT's responses in study cases in two scenarios.

- The initial answer did not accurately localize the root cause of the crash bugs (*e.g.*, crash bug 37771758).
- The initial answer identified the root cause of the crash bugs, but the solution provided was too general and did not offer specific resolution steps (*e.g.*, crash bugs 51370703 and 30322026).

For the first scenario, we devised New-Solution-Prompt to request new solutions; for the second scenario, we used Refinement-Prompt for the specific details of the solution.

During our attempts, we found that Refinement-Prompt can obtain solution details for most issues. However, for issues related to library versions, Refinement-Prompt was insufficient in obtaining specific version numbers that need to be upgraded or downgraded. Therefore, we designed specific prompts for such problems that require targeted questioning. For each crash bug, we employed both Basic-Prompt and Role-Play-Prompt in our experiments.

New-Solution-Prompt: I have tried the solution above, but the issue still remains. Can you give me some new solutions? **Refinement-Prompt:** Please provide more detailed information regarding the solutions mentioned above. **Version-Prompt:** Which version of [Library 1] is compat-

ible with my project/ [Library 2] version?

2) *Results:* Based on the specific analysis of the study cases and the results shown in Table III, we can draw the following conclusions (Findings 10-12), each with a detailed analysis.

| Table III   |
|---|
| EXPERIMENTAL RESULTS OF EXPLORING ADVANCE PROMPTS |

| Prompt                  | Rounds | Localization      | Repaired          | Solution<br>Num. | Usefulness   | Conciseness  | Interactivity |
|-------------------------|--------|-------------------|-------------------|------------------|--------------|--------------|---------------|
| Basic                   | Single | 46.7%             | 10.0%             | 5.8              | 1.6          | 1.5          | /             |
| Multi-Solution          | Single | 70.0%<br>(+23.3%) | 30.0%<br>(+20.0%) | 7.67             | 2.43 (+0.83) | 0.56 (-0.94) | /             |
| Role-Play               | Single | 76.7%<br>(+30.0%) | 33.3%<br>(+23.3%) | 5.23             | 2.83 (+1.23) | 1.87 (+0.37) | /             |
| Chain of Thoughts       | Single | 70.0%<br>(+23.3%) | 20.0%<br>(+10.0%) | 9.13             | 1.9 (+0.3)   | 0.2 (-1.3)   | /             |
| Basic + Multi-round     | Multi. | 83.3%(<br>+36.6%) | 53.3%(<br>+43.3%) | 4.77             | 2.93 (+1.33) | 2.17 (+0.67) | 3.37          |
| Role-Play + Multi-round | Multi. | 90.0%<br>(+43.3%) | 60.0%<br>(+50.0%) | 4.83             | 3.27 (+1.77) | 2.2 (+0.7)   | 3.63          |

**Finding 11**: Continuously interacting with ChatGPT can help to further improve its ability to localize and fix crash bugs.

Table III illustrates that continuous interaction enhances the model's performance in both localization and repair accuracy, as well as in scoring for usefulness and conciseness, compared to single-round interactions. Notably, even with the basic prompt in continuous interaction, the results surpass those of the most effective single-round role play prompt. This underscores the effectiveness of continuous interaction.

**Finding 12**: The use of Role-Play-Prompt significantly improves ChatGPT's ability to maintain contextual coherence and reduces instances of forgetting previous context, resulting in better resolving and interaction performance.

The experiments in Table III show that utilizing the Role-Play-Prompt for multi-turn interactions outperforms the basic prompt across all metrics. This suggests that the Role-Play-Prompt helps ChatGPT better understand the context and generate more accurate responses. Additionally, it significantly enhances the interaction score from 3.37 to 3.63. This improvement can be attributed to the Role-Play-Prompt aiding ChatGPT in maintaining contextual consistency and avoiding the repetition of previous solutions.

**Finding 13**: ChatGPT appears to have knowledge about library version that are discussed in official documentation. However, it requires targeted questioning to activate the corresponding knowledge.

Based on the trials conducted on crash bug 51370703, the above conclusion can be drawn as a supplement to finding 9.

To illustrate, if my inquiry about "Which version of SLF4J should I utilize?" during continuous interaction, ChatGPT might merely suggest updating to the latest version or even propose the use of version 1.8, as employed in the crash bug. However, if I raise the question "Which version of SLF4J is compatible with Logback 1.2.3 in my project?", it could stimulate knowledge that Logback version 1.2.3 necessitates slf4j-api version 1.7.x.

# E. RQ2.b: Enhancing Multi-round Prompts with Self-planning

From the above analysis, we find that ChatGPT struggles to accurately locate the root cause of a crash bug in a single attempt, even with the Role-Play Prompt and Chain-of-Thought prompt. This hampers its ability to provide targeted solutions. As discussed in Section IV-D and Finding 13, ChatGPT has knowledge to address many crash bugs, but accessing this knowledge requires specific methodologies. Continuous interaction and targeted questioning require the questioner to identify the true cause from potential solutions, placing high demands. Additionally, the absence of sufficient context from questioners restricts ChatGPT in offering targeted solutions (Finding 8), and questioners may be uncertain about relevant aspects of the comprehensive environment-related contexts for the crash bug.

To overcome these challenges, we empower the LLM to actively investigate potential crash-causing environmental factors through continuous proactive inquiry, guiding the resolution process step by step. Leveraging the LLM's self-planning ability [54], ChatGPT formulates an investigative plan targeting various environmental factors that could lead to crashes, prioritized based on their diagnostic significance. Actively seeking specific details from users, ChatGPT pinpoints the root cause step by step, providing targeted solutions. This objective is achieved through a **active inquiry** prompt designed to stimulate proactive questions from ChatGPT.

1) Design and Results: We used the role-play prompt to enable ChatGPT for active inquiry. We refined the questioning method to avoid overly general queries and prevent overwhelming developers with multiple questions simultaneously. This included specifying certain question types and providing an example to guide ChatGPT's questioning toward more targeted and actionable suggestions. The resulting prompt stimulates ChatGPT's proactive questions, facilitating selfplanning.

ActiveQ-Prompt: I want you to act as an program exception repair expert. You will be able to provide detailed solutions to fix the given program exception. Additionally, please use the Socratic method of questioning to aid in accurate diagnosis. But please note that the information in the question should be as specific as possible. For example, ... Also, only ask one question at a time, starting with the question you think is the

#### most important.

Upon evaluating ActiveQ-Prompt's performance, we noticed that ChatGPT may still generate multiple questions simultaneously, despite the instruction to ask only one question at a time. To address this, we introduce the AskOneQ-Prompt in subsequent interactions, emphasizing sequential singular question inquiries, prioritized based on their significance.

**AskOneQ-Prompt**: Note that only ask one question at a time, starting with the question you think is the most important.

By using this method, ChatGPT is able to ask one question at a time based on its priority, leading developers to targeted solutions. Utilizing the crash bug numbered 30322026 as an illustrative case, ChatGPT posed the following inquiry with the utilization of ActiveQ-Prompt and AskOneQ-Prompt:

My first question is: What is the version of the Smack library that you are using in this project?

After providing the corresponding information, partial Chat-GPT's response would be as follows:

To fix this issue, you can try using a Smack library version that is specifically designed for Android, such assmack-android-extensions: 4.4.4 'orsmack-android: 4.4.4'.

Based on the answer provided, it is evident that ChatGPT accurately pinpointed the underlying cause of the bug, which pertains to the incompatibility of the employed smack-java7:4.1.0 library with the Android environment. Furthermore, ChatGPT suggested a correct library version as the detailed solution.

**Finding 14**: Employing active inquiry prompts to stimulate proactive questions for self-planning enhances ChatGPT's ability to proactively guide the repair process. This aids in identifying the root causes of crash bugs, proving particularly beneficial for novice users.

## V. METHODOLOGY: INTDIAGSOLVER

Based on our experimental results and research findings, we introduce IntDiagSolver, a novel approach for resolving crash bugs through continuous interaction with a LLM. Figure 2 provides an overview of our approach. It's important to note that IntDiagSolver is not tied to any specific LLM and can be adapted as needed.

**Concept Explanations. Prompt provided by the users** is in a yellow box with crash details and instructions. The details of different prompts can be referred to the prompt templates listed in RQ1 and RQ2. **Response provided by LLMs** is in a blue box and can be categorized into questions and solutions. Questions may be multiple, but highlighting the question requirement will help ChatGPT generate a specific question (seeing section IV-E). Solutions can be rough or detailed (including optimized solution) with specific steps to fix the crash bugs. **Validation** is the repair attempt result in



Figure 2. Overview of Interactive Methodology for Crash Bug Resolution with LLMs

green box, which is currently manual. **Decision** in diamondshaped box indicating a selection, which based on manual judgment currently.

**Code-related Crash Bug Resolution.** To resolve code-related crash bugs, the main challenge lies in accurately diagnosis the root cause of crash bugs (refer to finding 3). Therefore, utilizing a Chain-of-Thought strategy to divide the resolution into diagnosis and repair stages is beneficial. This strategy entails deploying prompts to guide LLMs in identifying the buggy line, subsequently emphasizing the pinpointed information for efficient repair. Additionally, accentuating the exception type and providing a comprehensive crash context are instrumental in amplifying the effectiveness of the resolving (refer to finding 2).

**Environment-related Resolution.** Crash Bug For environment-related crash bugs resolving, users can choose to let LLMs guide the repair process. This is helpful for beginners with limited crash bug knowledge, while seasoned developers may not need LLMs' active guidance. Moreover, version issues present unique challenges as discussed in section III-B and finding 13. If users choose not to rely on LLMs' guidance, they should carefully examine the initial solution to identify any version issues. Version prompts should be utilized to elicit specific details in such cases. Additional, ordinary refinement prompts can suffice otherwise to obtain specific solution details.

**Validation Process**. Validation should be implemented after receiving LLMs' detailed solutions. If the solutions can fix the crash bug, the final correct solution will be obtained. Otherwise, new solution prompts should be utilized to obtain new solutions. This process entails a maximum number of attempts (*e.g.*, 3 in our setting).

Future Work. In the future, we aim to establish an end-to-

end automated plugin tool to accomplish the entire interactive process. This tool will automate crash bug type classification, prompt generation, analysis of LLM responses, and validation—executing repair attempts in the operational environment and providing automated feedback. Practical implementation could follow existing LLM-based interactive program repair methods [9].

#### VI. RQ3: EVALUATION OF INTDIAGSOLVER

To assess the effectiveness and generalizability of IntDiag-Solver, we conducted experiments for resolving crash bugs using this approach. Initially, we conducted experiments by integrating IntDiagSolver with ChatGPT, based on GPT-3.5, which we employed in RQ1 and RQ2 (as detailed in Section VI-A). Since IntDiagSolver was developed based on the insights from RQ1 and RQ2, our objective was to determine its efficacy in addressing the identified challenges and previously unresolved crash bugs from those studies. Furthermore, we extended our experiments to assess the generalization capability of IntDiagSolver by integrating it with various LLMs, including both open-source and closed-source state-of-theart ones (Section VI-B). This allowed us to evaluate how effectively IntDiagSolver performs across different LLMs.

# A. RQ3.a: Effectiveness of IntDiagSolver

In this RQ, we assess the effectiveness of IntDiagSolver in resolving crash bugs using GPT-3.5-based ChatGPT and compare it to a baseline scenario that employed with a basic prompt.

1) Setup: The experiment setup includes LLM configuration, benchmark, and metrics.

**LLM Configuration.** Using the same configuration as in RQ1 and RQ2 (Section II), we employed the gpt-3.5-turbo model [12] as GPT-3.5. Due to the model's non-deterministic nature, we conducted three individual runs for each crash bug, utilizing both the basic prompt and IntDiagSolver. A trial is considered successful if any individual run yields a positive outcome. Following the structure outlined in Section III-A2, each run initiates a new ChatGPT session to eliminate any influence from previous conversation histories.

**Benchmark.** From the initial 100-crash-bug benchmark in Section II-A, we deliberately chose unrepaired instances (see Table I) despite receiving complete crash descriptions. This selection forms a refined benchmark, comprising 11 code-related crash bugs and 30 environment-related crash bugs crashes, totaling 41 cases.

**Metrics.** The experiment's metrics align with those presented in Section III-A4. Additionally, to assess the effectiveness of continuous interaction, we record the number of interaction rounds required to achieve the final correct localization or repair result. If correct localization information is obtained in the first round, subsequent attempts without acquiring the correct repair information are still counted as one round. 2) Results: The results highlight substantial improvements in addressing both code-related crash bugs and environmentrelated crash bugs, with localization accuracy surging by 133.0% and 179.1% respectively. It is pertinent to note that the basic prompt yielded no successful repairs, rendering the calculation of accuracy unfeasible.

In addressing code-related crash bugs, 4 additional crash bugs were effectively localized and repaired. Three among these were repaired by emphasizing the buggy line in subsequent interactions, while highlighting the exception type in initial crash description facilitated one's localization. Concerning environment-related crash bugs, the improvement was more significant: 13 more bugs were accurately localized, and 16 more were successfully repaired. Furthermore, 14 crash bugs were resolved through iterative interactions, highlighting the efficacy of our IntDiagSolver framework.

#### B. RQ3.b: Generalizability of IntDiagSolver

In this RQ, we evaluate IntDiagSolver's generalizability on three additional LLMs, employing the same benchmarks and metrics as in RQ3.a (Section VI-A1).

1) Studied LLMs: We select three state-of-the-art LLMs: two closed-source models (GPT-4 [55] and Claude [56]) and an open-source model (Codellama-34b [57]). GPT-4, the latest in the GPT series and the successor of GPT-3.5, is a premier general LLM. Claude [56], developed by Anthropic, is a closed-source model with performance on the HumanEval dataset [58] surpassed only by GPT-4 and GPT-3.5 [59]. Codellama-34b [57], an enhanced version of Llama2 through additional code-specific training, is recognized as the leading open-source code LLM. To ensure experimental consistency, we maintain a uniform approach by conducting manual interactions through a web interface for all the studied LLMs.

2) Results: Table IV demonstrates IntDiagSolver's remarkable generalizability, effectively improving resolution for both code-related crash bugs and environment-related crash bugs across various closed-source and open-source LLMs when compared to the basic prompt. However, GPT-4, the most advanced LLM, exhibits only modest overall improvement, with a 13.1% increase in environment-related crash bugs localization accuracy and no improvement in code-related crash bugs, given its already high baseline performance. Moreover, all models exhibit more significant enhancement in resolving environment-related crash bugs (26.9% to 66.8% improvement) compared to code-related crash bugs, reflecting the complexities associated with environment-related crash bugs (as discussed in findings 1 and 5). Our efforts in Section IV primarily target environment-related crash bugs, resulting in more pronounced enhancements. Additionally, a noteworthy trend is the substantial improvement in repair accuracy compared to localization accuracy (ranging from 2.2% to 182.2%) more), highlighting the effectiveness of prompt enhancement in the repair stage.

Table IV RQ3 Experimental Results

| Model     | Туре         | Prompt        | Localization         | Repair               | Loc. with | Multi. | Localization    | Repair          |
|-----------|--------------|---------------|----------------------|----------------------|-----------|--------|-----------------|-----------------|
| iniouei   |              |               |                      |                      | Multi.    | Rounds | Accuracy        | Accuracy        |
| GPT-3.5   | Code Related | Basic Prompt  | 3                    | 0                    | 0         | /      | 0.273           | 0               |
|           |              | IntDiagSolver | 7 (+4)               | 4 (+4)               | 0         | 3      | 0.636 (+133.0%) | 0.364 (+/)      |
|           | Env. Related | Basic Prompt  | 12                   | 0                    | 8         | /      | 0.191           | 0               |
|           |              | IntDiagSolver | 25 (+13)             | 16 ( <b>+16</b> )    | 19        | 14     | 0.533 (+179.1%) | 0.271 (+/)      |
| GPT-4     | Code Related | Basic Prompt  | 9                    | 5                    | 3         | /      | 0.527           | 0.454           |
|           |              | IntDiagSolver | 9 ( <del>+0</del> )  | 6 ( <del>+</del> 1)  | 2         | 1      | 0.598 (+13.5%)  | 0.545 (+20.0%)  |
|           | Env. Related | Basic Prompt  | 21                   | 10                   | 21        | /      | 0.136           | 0.115           |
|           |              | IntDiagSolver | 25 (+4)              | 21 (+11)             | 19        | 9      | 0.223 (+64.0%)  | 0.231 (+100.9%) |
| Claude    | Code Related | Basic Prompt  | 5                    | 4                    | 2         | /      | 0.336           | 0.291           |
|           |              | IntDiagSolver | 6 ( <del>+</del> 1)  | 5 (+1)               | 2         | 1      | 0.386 (+14.9%)  | 0.341 (+17.1%)  |
|           | Env. Related | Basic Prompt  | 12                   | 5                    | 12        | /      | 0.117           | 0.083           |
|           |              | IntDiagSolver | 18 ( <del>+6</del> ) | 13 ( <del>+8</del> ) | 13        | 8      | 0.211 (+80.3%)  | 0.194 (+133.7%) |
| Codellama | Code Related | Basic Prompt  | 4                    | 2                    | 0         | /      | 0.364           | 0.181           |
|           |              | IntDiagSolver | 6 (+2)               | 4 (+2)               | 0         | 1      | 0.545 (+49.7%)  | 0.364 (+101.1%) |
|           | Env. Related | Basic Prompt  | 7                    | 2                    | 6         | /      | 0.111           | 0.051           |
|           |              | IntDiagSolver | 12 (+5)              | 9 (+7)               | 8         | 7      | 0.196 (+76.6%)  | 0.183 (+258.8%) |

#### VII. RELATED WORK

### A. LLMs for Software Engineering

In recent years, LLMs have gained considerable attention across various research domains, including mathematics [13], [14], education [15], [16], and natural language processing [17], [18]. In the field of software engineering (SE), LLMs have demonstrated their potential by being applied to a wide range of tasks, from code generation [21], [22], [23] and code summarization [19], [20] to software maintenance tasks, including vulnerability detection [38], [60], test generation [61], [62], and program repair [7], [26], [9], [63], [64]. This broad SE application stems from their robust training on extensive code and text data, enhancing both linguistic and code comprehension.

## B. LLMs for Resolving Crash Bugs

Software crashes pose an enduring challenge in software development, driving research in areas such as crash reproduction [65], [66], crash localization [67], [68], [69], and crash repair [2], [3], [10]. Efforts to tackle code-related crash bugs have resulted in research on automatic localization [4], [5], [6] and repair [7], [8], [9]. In contrast, environment-related crash bugs, due to their diverse origins, often rely on solutions from online Q&A forums like SO [3], [10], [11], [70].

Recent surveys on LLMs in software engineering [71], [72] have explored their applications, performance, and challenges, including bug localization and program repair. Preliminary studies [26], [9], [63] on ChatGPT's potential in addressing code-related bugs have primarily focused on simple scenarios with fixed prompts. In contrast, our study: (i) diverges from existing work by categorizing the resolution process into two stages: localization and repair, (ii) comprehensively assesses ChatGPT's effectiveness in resolving real-world crash bugs sourced from SO, (iii) explores the effects of different prompts in various interaction strategies, and (iv) notably extends beyond code-related problems to include crash bugs caused by external environmental factors, an aspect that has received limited attention in prior research.

## C. Prompt Engineering for Software Engineering

Prompt engineering is an emerging discipline that optimizes prompts for various applications of LLMs across different domains. Methodologies in this field include Few-Shot Prompting [73], Chain-of-Thought Prompting (CoT) [52], [53], Treeof-Thoughts (ToT) [74], and Knowledge Prompting [75]. In software engineering domain, prompt engineering enhances LLMs in various tasks. Researchers have used Chain-of-Thought Prompting to improve code generation [76], [77], explored argumentation and task decomposition strategies for better unit test generation [61], and combined Chainof-Thought Prompting with static analysis for more efficient vulnerability detection [60]. Additionally, Knowledge Prompting integrated with a Tree-of-Thoughts approach has advanced LLMs in database diagnostics [78]. In this study, we explored various prompt templates and advanced techniques to effectively resolve crash bugs. To this end, we propose IntDiagSolver, employing Knowledge Prompting to resolve crash bugs. It breaks the process into two phases (localization and repair) with multi-turn interactions involving LLMs, following the principles of Chain-of-Thought Prompting.

# VIII. THREATS OF VALIDITY

The study used a dataset of 100 Java-related crash bugs from SO, which might limit generalizability. To address this, the researchers deliberately selected a diverse range of realworld crash bugs, including both code and environment-related issues. Focusing on Java crash bugs was due to their prevalence and significance in program repair research [3], [10], and prior studies [63] have shown LLMs' transferability across programming languages, reducing language-related concerns. To improve generalizability in future research, considering larger and more diverse datasets from various programming languages and software systems could be beneficial.

In our exploratory study (RQ1 and RQ2), GPT-3.5's use may limit generalizability of our findings and the applicability of IntDiagSolver approach to other models. To address this, in RQ3, we tested our method on GPT-4 and other LLMs, reinforcing our initial findings and indicating potential applicability to other models. Additionally, a potential threat in RQ2 is the use of only 10 cases for interaction exploration, possibly introducing bias. Nevertheless, practical tests in the evaluation phase demonstrated promising effectiveness across a broader range of cases (Table IV).

Due to the stochastic nature of ChatGPT's responses, there may be an impact on the experiment's reliability and validity. To mitigate this, we performed multiple trials and meticulously documented all ChatGPT interactions for transparency and reproducibility [79]. A potential threat involves the risk of data leakage from the SO benchmark. Despite ChatGPT not disclosing its training data, insights from previous research [61] and our own comparisons with the ground truth suggest that, even as a state-of-the-art LLM, ChatGPT has not merely memorized the data used in our study.

# IX. CONCLUSION

This study empirically investigates ChatGPT's effectiveness in localizing and repairing software crash bugs. It also investigates strategies to enhance interaction for improved bug resolution accuracy and efficiency. Leveraging experimental findings, we introduce IntDiagSolver, a methodology that optimizes the interaction process and prompt design when working with LLMs for crash bug resolution. Results underscore ChatGPT's significant role, showcasing notable improvements in resolution accuracy and efficiency through optimized processes. In summary, this study provides developers with a new method for resolving crash bugs using LLMs, offering insights for optimizing the interactions with these models.

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