

# Past, Present, and Future of Bug Tracking in the Generative AI Era

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Traditional bug tracking systems rely heavily on manual reporting, reproduction, triaging, and resolution. These tasks are performed by different stakeholders such as end users, customer support, developers, and testers. This division of responsibilities requires significant coordination in addition to the considerable human time and effort. This reliance widens the communication gap between non-technical end users and technical developers, slowing the process from bug discovery to resolution and deployment. Moreover, current solutions tend to be highly asynchronous; end users often wait hours, days, or even weeks before receiving an initial response, further delaying fixes and contributing to frustration.

In this paper, we examine the evolution of bug tracking practices, moving from early paper-based and manual reporting methods to today's web-based and software as a service (SaaS) platforms that dominate modern software development. Building on this trajectory, we outline our vision for the future: an AI-powered bug tracking framework that augments existing systems with intelligent, large language model (LLM) driven automation.

Our approach tackles two main challenges: reducing the time to resolution (TTR) and minimizing coordination overhead by bridging the gap between end-users and developers. In the proposed framework, end users report bugs in natural language. AI-driven agents refine these reports, attempt to reproduce them, and request missing details, if any. Bug reports are classified according to their type. Invalid bugs are automatically classified and either dismissed or resolved via no-code fixes suggested by agents. Valid bugs, once confirmed, are localized and assigned to developers, who review LLM-generated patches and verify their correctness. Verified patches are deployed using continuous integration and continuous development (CI/CD) pipelines, which are already generated and maintained by the LLM agents.

This paper presents our vision for an AI-powered bug tracking framework, highlighting the challenges and opportunities of integrating LLMs into bug tracking. By positioning our framework as both a forward-looking design and a practical augmentation for existing bug tracking tools, we try to illustrate how automation not only decreases response times and TTR but also transforms the overall software maintenance process, paving the way for a more efficient, collaborative, and user-centric future.

**CCS Concepts:** • Software and its engineering → Software maintenance tools; • Artificial intelligence → Intelligent agents.

**Additional Key Words and Phrases:** Bug Tracking, Large Language Models, AI-Driven Software Maintenance, AI-Powered Software Engineering, Bug Reports, AI-Powered Bug Tracking

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## 1 Introduction

Bug tracking is a fundamental process in software maintenance, ensuring software quality, reliability, and long-term sustainability [68]. The concept of software bugs dates back to the early days of computing, with the famous case of a moth causing a malfunction in the Harvard Mark II computer in 1947, often cited as the first recorded bug [110]. Since then, the occurrence of defects in software systems has been recognized as an inevitable aspect of development, prompting the establishment of systematic practices to identify, document, and resolve issues. Early approaches to bug tracking were predominantly manual, involving handwritten logs, spreadsheets, or informal communication among developers [57]. As software engineering matured, the growing scale and complexity of systems required more structured methods, leading to the development of dedicated bug tracking systems in the late 20th century [95]. These systems introduced standardized reporting formats, status tracking, and mechanisms for assigning responsibility, creating a more disciplined process for bug tracking.

Over time, bug tracking has evolved into an essential backbone of collaborative software development, becoming integrated into broader software engineering workflows. Modern bug tracking practices emphasize traceability and coordination among diverse stakeholders [5], enabling teams to track the entire lifecycle of a bug, from discovery and reporting to resolution and verification. Bug tracking repositories now serve not only as records of defects but also as valuable sources of knowledge, informing project management decisions, supporting quality assurance, and guiding future development [158]. Despite these advancements, the fundamental manual nature of bug tracking has remained largely unchanged. Thus, problems might arise in the names of communication problems, ambiguous bug reports [158], and the need for extensive human intervention [4].

As the volume of reported bugs grows with the scale of software projects, the importance of efficient and reliable bug tracking systems has become more pronounced, solidifying their role as a critical enabler of software quality assurance [50, 51]. Widely used bug tracking tools such as Jira<sup>1</sup>, Bugzilla<sup>2</sup>, and GitHub Issues<sup>3</sup> have played central roles in software engineering. Jira, released in 2002, has become a dominant system in enterprise settings for handling bugs, tasks, and project management workflows. Bugzilla, publicly available since 1998, has been used in many open source projects as one of the canonical issue tracking platforms, particularly for its flexibility and openness. GitHub Issues has also emerged as one of the most widely used bug tracking systems in open source communities. These tools are used widely across open source communities and proprietary organizations, often acting as the canonical system for bug reporting, triage, assignment, status tracking, historical analysis, and the communication channel for the stakeholders.

However, despite their maturity and widespread adoption, these systems have notable deficiencies. Jira and Bugzilla often impose overhead by requiring detailed workflow configuration and many mandatory fields, which can slow down bug reporting and triage. For example, Jira users have complained about performance and usability issues, like the system slowing down when workflows get too complex<sup>4</sup>. In contrast, GitHub Issues has been criticized for its unstructured design. Empirical

<sup>1</sup><https://www.atlassian.com/software/jira>

<sup>2</sup><https://www.mozilla.org/>

<sup>3</sup><https://github.com/features/issues>

<sup>4</sup><https://jira.atlassian.com/browse/JRASERVER-61704>

studies show that many issues are created without sufficient context, lacking reproducible steps or environment details [108]. Software maintainers often cannot, or choose not to, enforce strict templates or workflows in many repositories. For example, a study on large GitHub projects [119] found that the ontology of issue templates and required metadata is either minimal or inconsistently used, leading to ambiguity in many reports. These deficiencies result in several inefficiencies, including duplicate reports, slower triage and resolution, inconsistent issue quality, and higher manual efforts.

The recent rise of large language models (LLMs) such as Gemini [26], GPT [1], and Llama [121] has transformed natural language processing by enabling machines to generate, understand, and reason over text at unprecedented levels of fluency and accuracy. Leveraging massive pre-training on diverse text corpora, these models demonstrate remarkable zero-shot and few-shot capabilities, generalizing across a wide variety of tasks without requiring task-specific training. Beyond research benchmarks, LLMs are increasingly deployed in real-world applications such as conversational assistants, code generation, and knowledge management, fundamentally changing the way humans interact with software systems. Their ability to interpret unstructured inputs, extract structured information, and produce contextually relevant outputs suggests strong potential for integration into complex workflows that usually exist in software engineering. GitHub Copilot<sup>5</sup>, for instance, has already shown how LLMs can be used in programming tasks by providing real-time code suggestions, signaling a shift toward AI-augmented software development [122].

Beyond standalone LLMs, researchers are increasingly focusing on LLM agents, autonomous or semi-autonomous systems that can understand their environment, plan tasks, and carry out actions to achieve long-term goals [131]. These agents can be combined into multi-agent systems, where multiple LLMs collaborate through structured communication, task specialization, and coordination protocols [56, 99]. Such orchestration allows agents to complement each other, mitigate individual weaknesses, and scale to solve more sophisticated problems than a single model could handle in isolation. Frameworks such as AutoGPT<sup>6</sup> and MetaGPT<sup>7</sup> exemplify this direction, where agents assume distinct roles (e.g., planner, coder, tester) and cooperate to achieve complex objectives. The emergence of these paradigms highlights the feasibility of constructing collaborative ecosystems of LLMs that can continuously refine, validate, and operationalize knowledge in dynamic domains.

Although there are some studies on this topic, the integration of LLMs into bug tracking is still relatively underexplored. Nonetheless, it remains an important direction because traditional methods often face communication problems<sup>8</sup>, slow issue resolution<sup>9</sup>, and high manual effort<sup>10</sup>, as shown in the footnoted examples. While recent works have applied LLMs to some tasks in bug tracking, such as bug localization [90, 139] and program repair [98, 157], others have explored their use in broader software engineering activities [52, 58, 100]. Yet, the integration of LLM agents into the end-to-end bug tracking lifecycle, from bug report generation to bug verification and patch deployment, has not been systematically studied. Moreover, the potential of collaborative LLM agents to act as automated triagers, verifiers, or explainers of bug reports has yet to be fully realized. This gap presents a promising research opportunity to reimagine bug tracking systems by embedding LLMs and multi-agent collaboration into their core, thereby reducing manual effort, improving report quality, and accelerating defect resolution.

<sup>5</sup><https://github.com/features/copilot>

<sup>6</sup><https://github.com/Significant-Gravitas/AutoGPT>

<sup>7</sup><https://github.com/FoundationAgents/MetaGPT>

<sup>8</sup><https://github.com/huggingface/transformers/issues/39803>

<sup>9</sup><https://github.com/huggingface/transformers/issues/17283>

<sup>10</sup><https://github.com/huggingface/transformers/issues/40136>

In this article, we introduce a visionary AI-powered framework that leverages LLMs to automate key aspects of the bug tracking process. Our framework enables users to report bugs in natural language, allowing AI-driven automation to assist in reproduction, classification, validation, resolution, and verification. By reducing reliance on manual triaging and streamlining communication, our approach would enhance efficiency while maintaining human oversight where necessary, and decrease time to resolution (TTR).

By automating repetitive and time-consuming tasks and bridging the end-users, who are usually non-technical, and the technical developers, our vision significantly reduces the time and human effort required for bug triaging and resolution. It also addresses communication issues<sup>11</sup> that often arise during bug tracking. Through automation, we aim to minimize human involvement in repetitive tasks<sup>12</sup> that typically happen during bug tracking while maintaining high accuracy and efficiency in bug resolution. We discuss the potential challenges and long-term research opportunities in integrating AI-driven automation into software maintenance workflows, specifically in bug tracking. We envision a future where AI and human collaboration, within a human-in-the-loop (HIL) system, redefines software maintenance.

In the following sections, we first explain the historical evolution of bug tracking systems from early solutions to the contemporary bug tracking systems with their limitations in Section 2, our proposed bug tracking framework in Section 3, then, we discuss the possible implications and open challenges in Section 4. We conclude our study in Section 5.

## 2 Historical Evolution and Current System of Bug Tracking

This section provides an analysis of the bug-tracking process, from its foundational principles to its modern implementations. Section 2.1 reviews the evolution of bug tracking systems, showing how early manual approaches provided the foundation for today's advanced platforms. Section 2.2 describes the architecture and workflow of the current bug tracking systems, detailing their key components and how they function within the software development lifecycle. Finally, Section 2.3 critically evaluates the challenges of these current systems, identifying the challenges and inefficiencies.

### 2.1 Historical Evolution of Bug Tracking Systems

The evolution of bug tracking systems reflects the broader maturation of software engineering practices, moving from informal, ad hoc issue recording methods to sophisticated, collaborative platforms integrated across the software development lifecycle. Understanding this trajectory is crucial to identifying current limitations and informing the design of next generation systems. In the following, we explain bug tracking eras, which are divided according to their key technological aspects and innovations. Table 1 displays each era and its characteristics.

**2.1.1 Early Digital Era (1940s-1970s).** In the earliest days of software development, bug tracking was a manual, often paper-based process. Developers recorded errors in logbooks or simple text files. These methods lacked structure and traceability, offering no systematic way to categorize, prioritize, or assign bugs. For instance, during the operation of ENIAC [116], the most common errors were notational, arising from inconsistencies among redundant specifications of the same detail. Also, there were concurrency errors, which were resolved by adjusting the timing of control signals, often by inserting a dummy program to delay a signal. As projects grew in scale and complexity, manual tracking became untenable [102].

<sup>11</sup><https://github.com/huggingface/transformers/issues/39803>

<sup>12</sup><https://github.com/huggingface/transformers/issues/40136>

**2.1.2 Pre-Internet Era (1970s-1980s).** During this period, communication began to evolve beyond face-to-face meetings. Email systems<sup>13</sup><sup>14</sup>, simple databases like dBase<sup>15</sup>, and early file-sharing networks emerged. Bugs were often reported by users via email or phone calls to customer support. The software itself was shipped on floppy disks, and users would sometimes mail back faulty disks along with registration forms. When a customer support representative received a bug report, they would write the reproduction steps into a text file. This file would then be passed to a developer who would manually try to reproduce the bug. Fixing a bug involved manual code changes, which were then shared with the customer via a new floppy disk or, if available, a local network. Verification was done through manual testing with a documented checklist. The process was very slow and inefficient. While remote communication was a new development, collaboration was still low, often leading to a high TTR.

**2.1.3 Internet Era (1980s-1990s).** This era saw the first dedicated bug-tracking systems. Tools like GNATS (GNU Bug Tracking System)<sup>16</sup>, Debuggs<sup>17</sup>, and CMVC [152] were introduced. GNATS, for instance, was an early, open source bug tracking system that used text-based files and email for communication, providing a structured interface for logging and tracking bugs. Debuggs was the software powering the Debian project's issue tracking system. It did not have any form of web interface to edit bug reports, all modification was done through email. These systems allowed for detailed reproduction steps to be logged and were accessible to the whole team. When a bug was fixed, the code was committed to a version control system (VCS), and the bug report was updated with details about the fix.

As software development matured, teams began to adopt formal processes. Developers and quality assurance (QA) engineers tracked basic bug statistics such as the number of new bugs opened, bug close rates, and fix versus invalid rates.

To manage the bug backlog, Netscape<sup>18</sup> team leaders held weekly bug meetings, or "bug councils". As the project neared its release, these meetings increased in frequency to once or twice a day to prioritize and make decisions on fixes. These meetings were typically led by a project or release manager and included representatives from development, QA, and marketing teams. Netscape used a five-level classification system: critical, major, normal, minor, and trivial. Bugs were classified and entered into the database by the engineers who found them, typically from the QA team. The marketing team also maintained a "top 10 bugs" list based on customer feedback, which was passed to QA [28]. By the mid-to-late 1990s, centralized client-server tools began to surface, offering more structured workflows.

**2.1.4 Web-Based Era (2000s).** This decade saw a major shift to web-based platforms. Tools like Bugzilla, MantisBT<sup>19</sup>, Trac<sup>20</sup>, and early versions of Jira emerged. Bugzilla became a landmark open source system. Bugzilla introduced key abstractions still in use today, including structured fields (e.g., severity, priority, component), status transitions, and user roles. It provided a web-based interface and notification mechanisms, enabling better coordination among developers and testers [96]. These systems treated bug reports as work items in a sprint, integrating with the emerging agile methodologies. The web UI made it much easier for everyone to access and track bugs.

<sup>13</sup><https://en.wikipedia.org/wiki/ALL-IN-1>

<sup>14</sup>[https://en.wikipedia.org/wiki/IBM\\_OfficeVision](https://en.wikipedia.org/wiki/IBM_OfficeVision)

<sup>15</sup><https://www.dbase.com>

<sup>16</sup><https://www.gnu.org/software/gnats/>

<sup>17</sup><https://en.wikipedia.org/wiki/Debuggs>

<sup>18</sup><https://isp.netscape.com/>

<sup>19</sup><https://mantisbt.org/>

<sup>20</sup><https://trac.edgewall.org/>

The expansion of community-contributed plug-ins and themes also reflected the diverse needs of development teams, from small startups to large open source foundations [11]. Collaboration improved with shared dashboards and email notifications, though bottlenecks were still common due to a lack of deep integration with development tools [36].

**2.1.5 Software as a service (SaaS), DevOps and Automation Era (2010s-2022).** In this era, platforms like GitHub Issues, GitLab Issues<sup>21</sup>, YouTrack<sup>22</sup>, and Azure DevOps<sup>23</sup> became the standard. Bug tracking became fully integrated into the development lifecycle. GitHub Issues, for example, is part of a larger ecosystem that includes version control and continuous integration. Fixes were no longer just committed; they became a part of a Continuous Integration/Continuous Deployment (CI/CD) pipeline, where code changes automatically trigger tests and deployments.

The growing popularity of issue-driven development, where code commits are directly tied to issue identifiers, further solidified the role of bug tracking systems as central elements of the software delivery process. Developers began to view bug tracking systems not merely as databases of bugs, but as vital components of planning, communication, and accountability [15, 46].

Parallel to industry adoption, academic research began to explore how Machine Learning (ML) techniques could improve the efficiency of bug tracking processes [101]. Early studies applied text classification and clustering algorithms to automate tasks such as duplicate detection, severity prediction, and assignee recommendation [20, 78]. These contributions laid the groundwork for more intelligent and data-driven approaches to defect management.

Table 1. Summary of Bug Tracking Eras

Era	Bug Reporting	Bug Reproduction	Bug Fixing	Verification	Bug Classification Support	Representative Tools	What is New?
Early Digital Era (1940s-1970s)	Bugs were written to the notebooks, sticky notes, spreadsheets, etc.	There are a certain number of testing methods in the system, and with these testing methods, the bug is reproduced.	For notational bugs, bugs are fixed by correcting the wrong place in the notebook. For the concurrency bugs, the bugs are fixed by using a dummy program to adjust the signals.	The same methodology as the Bug Reproduction. If all tests are passed, then the bug is verified.	Bug types or severity are not consistently captured	Paper Logs, Index Cards, Notebooks	NA
Pre-Internet Era (1970s-1980s)	Reported via email/phone or customer support. Software shipped on floppy disks with registration forms; users mailed forms and faulty disks back to developers.	Customer support receives bug reproduction steps from the user via email or phone call, then writes these steps to the text file. Then these steps are passed to the developer to reproduce the bug.	Manual code changes, shared via floppy disk or a local network.	Manual testing, often with a documented checklist.	Simple severity labels, often inconsistently used	Email, text editors, simple databases (e.g., dBBase), network file shares, Lotus 1-2-3. <sup>24</sup>	Introduction of remote communication for bug reporting (email, phone) and use of digital storage for transferring software and fixes.
Internet Era (1980s-1990s)	Reports were logged into the system by a user with some structure.	Detailed Steps to Reproduce (S2R) were logged in the system, accessible to the whole team.	Code fixed and committed to VCS. Updates were often manual in the bug report.	Formal QA teams re-tested fixes; verification was largely manual and sequential.	Simple severity labels, often inconsistently used	GNATS, Debuggs, CMVC	Structured digital bug databases introduced, enabling team-wide visibility and linking bugs to code changes.
Web-Based (2000s)	Web UI support, bug reports were treated as work items in a sprint	Detailed S2R were logged in the system, accessible to the whole team.	Fixes tied directly to modern VCSs (Git, etc.). Systems started auto-linking commits/pull requests to bug reports.	QA remained formalized but incorporated automation (test scripts, regression suites) and parallel workflows.	Manual categorization with some automation	Bugzilla, MantisBT, Trac, Redmine, Jira, Microsoft Team Foundation Server (TFS)	Shift to web-based collaboration, integration with Agile workflows, and more formalized bug management processes.
SaaS, DevOps and Automation Era (2010s-2022)	Web-based, collaborative platforms integrated with other development tools.	Logs/screenshots attached to tickets; testing environment integration became standard	Fixes were part of a CI/CD pipeline. Fixes were tracked via VCSs.	Automated testing became a standard practice, with test results often linked directly to the bug ticket.	Tagging, priority queues, category rules	GitHub Issues, GitLab Issues, YouTrack, Azure DevOps	Fully integrated bug tracking into DevOps toolchains with CI/CD, automated testing, and real-time collaboration.

## 2.2 Current System

Figure 1 presents a typical workflow of the traditional (SaaS, DevOps, and Automation Era) bug tracking system, showing the interactions among different roles. The process starts when a user creates a bug report. Customer support then attempts manual bug reproduction. If reproduction is unsuccessful, additional details are requested from the user, and the attempt is repeated until the

<sup>21</sup><https://docs.gitlab.com/user/project/issues/>

<sup>22</sup><https://www.jetbrains.com/youtrack/>

<sup>23</sup><https://azure.microsoft.com/en-us/products/devops>

<sup>24</sup>[https://en.wikipedia.org/wiki/Lotus\\_1-2-3](https://en.wikipedia.org/wiki/Lotus_1-2-3)

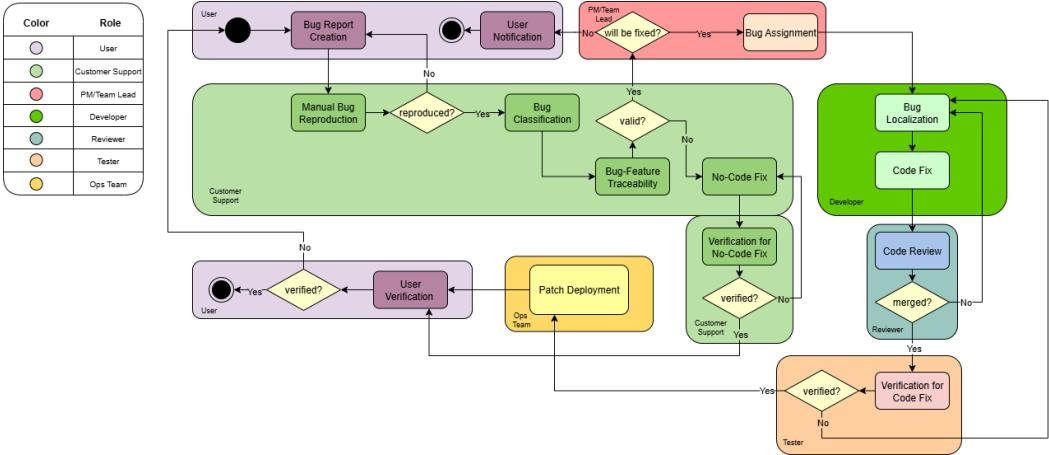


Fig. 1. Overview of Traditional Bug Tracking System Workflow

bug can be reliably reproduced. Once reproduction is successful, the bug proceeds to classification. After classification, a bug–feature traceability step is performed, followed by the validity check. In the traditional literature, classification and assignment together are often referred to as “bug triage,” but in our discussion, we separate these into two distinct stages: classification and assignment.

If the bug is invalid, customer support attempts what we call a no-code fix, meaning a resolution handled outside the codebase, for example, updating documentation, adjusting configurations, or clarifying usage. This resolution is then verified by customer support, and if verification succeeds, the user is directly notified and asked to confirm whether the resolution is acceptable, which we call user verification. If customer support verification fails, the process returns to the no-code fix stage, where customer support attempts another resolution until the issue can be successfully verified.

For valid bugs, the Project Manager (PM) or team lead determines whether the issue should be addressed. A negative decision results in the user being notified, while a positive decision leads to the bug being assigned to a developer. The developer first performs bug localization and then applies a code fix. After the fix, the change enters the code review stage. If the reviewer does not approve the fix, it cycles back to the developer; if it is approved, the fix moves to the verification stage.

The tester verifies whether the code fix has resolved the bug. If the verification fails, the process returns to the developer; if it succeeds, the workflow continues with patch deployment carried out by the operations team. Once the patch is deployed, user verification serves as the final step. If the user confirms the fix, the process ends successfully; if not, the workflow loops back for further handling.

### 2.3 Challenges of Current System

Given the traditional bug-tracking process described above, it is important to examine the key challenges that hinder its effectiveness. While the primary objective is to identify and resolve bugs within an intended time span, the whole process, which starts with bug reporting and ends with final deployment and user verification, faces many obstacles. These issues are not just caused by technical reasons; they often arise from human factors [120, 158]. In the following, we have summarized the key challenges.

**2.3.1 Challenges of Initial Bug Report Creation.** The bug-fixing process is fundamentally tied to the quality of the information provided in the bug report, which is one of the cornerstones of a bug tracking system. A primary challenge is that information in these reports is often incomplete or vague [17, 120, 158]. This can lead to reports that lack clear reproduction steps and crucial environmental details. Missing environment variables, such as product version and operating system (OS) version in a report, and missing severity are two examples of bug tracking process smells [103], specifically about bug reports. As a result of these bad practices, customer support staff and developers are forced to engage in a time-consuming "ping-pong" of communication with the reporter, requesting additional information [103]. This back-and-forth exchange significantly slows down the bug resolution process and increases the number of unresolved issues [159]. The problem is often compounded by the passive nature of traditional bug tracking systems, which are little more than interfaces for relational databases and offer minimal support for reporters to provide the necessary context [159]. In addition, reporters who are not technically experienced may struggle to articulate problems in a structured way or find bug tracking interfaces difficult to use, further reducing the clarity and usefulness of bug reports.

**2.3.2 Challenges of Bug Reproduction.** Once a bug is reported, the next step is consistently reproducing it in a controlled environment. This task can be surprisingly difficult due to several reasons, such as discrepancies between the original user environment and the development environment or lack of information in the bug report [84, 124]. Bugs that are not raised during obvious conditions can increase the challenge of reproducibility. There are bugs called Heisenbugs [48] that change their behavior or disappear entirely when debugging or observing them, making them difficult to reproduce [59]. Bugs that are caused by concurrency issues can be given as an example to this class. The rate of non-reproducible bugs is far from negligible; in their study, Goyal et al. [47] mined bug reports from four large-scale open source software projects of the Bugzilla repository and found that non-reproducible bugs range from 12.77% to 24.26% of all reported bugs. Failing to reliably reproduce an issue often leads to frustration and wasted effort for both the development team and users.

**2.3.3 Challenges of Bug Classification.** Manual classification is labor-intensive and time-consuming, which involves a series of sequential actions, demands substantial problem-solving abilities and careful consideration. The large volume of incoming bug reports can easily overwhelm teams, leading to a mounting backlog of issues and significant delays in the software development lifecycle [73]. Reports often contain incomplete information and ambiguous descriptions [13], which may complicate accurate classification.

Another persistent challenge is subjectivity, particularly in the critical steps of assigning severity and priority. Different team members may interpret the same symptoms differently, causing inconsistencies in triage decisions. To mitigate this, many teams adopt structured frameworks or agreed-upon taxonomies to align technical and business assessments of a bug, which is hard to maintain.

**2.3.4 Challenges of Traceability of Bugs to Other Artifacts.** Traceability of the bug is the ability to trace it in the whole bug lifecycle using artifact links. Examples for these artifacts can be bug fixing commits [106] and Pull Request (PR) of the bug fix [149]. Due to a lack of set rules and oversight, developers often fail to link their PRs to the specific issues they are meant to solve [107]. This disconnect makes it difficult to understand why certain code was changed, leading to a loss of valuable information that could be useful when problems arise. Another important aspect is Requirements Traceability (RT), which refers to the ability to track and follow the life of a requirement across the project lifecycle [45]. RT links are valuable during maintenance because

they allow developers to quickly understand the impact of changes, trace defects back to their originating requirements, and ensure that modifications remain consistent with stakeholder needs. However, creating and maintaining these links is laborious, as it often requires manual effort to analyze requirements, design artifacts, code, and test cases, and then establish explicit relationships between them. Lack of traceability can raise problems in the future of that software project, such as the reduced effect of change impact analysis [9]. Automated techniques to construct these links would save resources.

**2.3.5 Challenges of Detecting Invalid Bugs.** Another possible challenge is to detect if the bug is valid or not. Some of the causes of invalid bugs are insufficient background knowledge, misunderstanding of functionality, misunderstanding of environment, error in testing, and error in the external system, according to Sun et al. [120].

While automated bug classification of valid/invalid bugs using ML has shown promise in reducing manual effort, its adoption faces several practical challenges. A major issue is the quality and imbalance of real-world bug datasets. Projects often contain a large proportion of non-bug or duplicate reports compared to true defects, which biases models toward the majority classes and reduces performance on the more critical minority classes. Beyond imbalance, bug reports themselves are highly heterogeneous: they may be written in natural language with varying levels of detail, include incomplete or noisy information, or use project-specific jargon that makes feature extraction difficult. Additionally, labeling ground truth data is labor-intensive and prone to human inconsistency, further limiting the reliability of training data. These challenges collectively highlight why practical deployment of automated bug classification remains non-trivial despite promising research results.

**2.3.6 Challenges of Bug Localization.** A primary challenge in debugging is the initial task of identifying the root cause of an issue. This can be a challenging task, especially in large and complex codebases where developers must sift through a large number of potential culprits to find responsible lines of code [43]. The difficulty is compounded in modern environments by the distributed and interconnected nature of applications, where issues may traverse multiple system layers and require expertise with a range of specialized tools [43].

**2.3.7 Challenges of Creating Bug Fix.** While a bug might be identified and its root cause understood, the actual process of changing the code is far from trivial. Typically, a change made to a software system may result in an undesirable side effect or ripple effect to the rest of the system [7]. There is a unique set of challenges that can impact code quality, introduce new defects, code smells, and increase the overall cost of development. Changed code might affect other parts of the code, which is challenging to detect, as change impact analysis is being used to measure the side effects of code changes using several metrics [44]. Lack of documentation might cause challenges in the code change process as well. Without clear documentation, developers may not understand why a particular piece of code was written a certain way.

**2.3.8 Challenges of Bug Fix Verification.** Verifying a bug fix is the final, critical step in the bug-fixing lifecycle. It is the process of confirming that the bug is truly resolved and that the fix has not introduced any new problems. The primary technical challenge in bug fix verification is the risk of regression. A bug fix, especially in a complex system, can inadvertently break existing, previously functional code. This requires testers to go beyond merely checking if the original bug is fixed and perform extensive regression testing, which can be time-consuming and difficult without robust automated test suites. Another technical challenge in this step is reproducibility, which is also a challenge mentioned in Section 2.3.2. The scope of testing is also a challenge, as a tester must correctly identify all the areas of the application that could have been affected by

the fix, a task that becomes exponentially more difficult with tightly coupled code and a lack of clear documentation. Beyond the technical aspects, bug fix verification is significantly affected by human and organizational factors. Deak et al. [29] show that testers are affected by negative factors categorized as: lack of influence and recognition, unhappy with management, technical issues, lack of organization, time pressure, boredom, poor relationships with developers, and working environment issues.

**2.3.9 Challenges of Asynchronous Communication.** In modern bug tracking workflows, much of the interaction between stakeholders takes place through asynchronous communication that is, exchanges like emails, issue comments, or chat messages that do not require participants to be online at the same time. The primary challenge of using asynchronous communication is the inherent lack of real-time context and immediate feedback. Unlike synchronous methods such as live meetings or screen shares, asynchronous bug reporting and resolution can lead to significant delays [36]. A developer may need to ask for more information about the bug, such as specific S2R for it or screenshots from a different browser, but the response may not come for hours or even days. This time lag, often referred to as communication latency or communication gap, can stall the entire bug-fixing process and cause a loss of momentum [36]. It also makes it difficult to have a nuanced, back-and-forth discussion, which is often necessary to fully understand and diagnose a complex issue. Study [69] shows that when the reliance on asynchronous tools increases, the software defect rates increase accordingly.

### 3 AI-Powered Bug Tracking Framework

To mitigate the problems of the current bug tracking systems that are detailed in Section 2, we propose a visionary bug tracking framework leveraging LLM/AI agents. We address some of the limitations highlighted in the previous section, from the subjectivity and inefficiency of manual bug reporting and classification to the complexities of bug localization and the risk of regression during fix verification. By integrating LLM/AI agents into bug tracking, we aim to enable automation and intelligence at multiple stages of bug tracking. LLMs' role begins with assisting in bug report creation and enhancement and continues through reproduction, classification, traceability link creation, validation, bug assignment, localization, fixing, verification, and deployment.

#### 3.1 Overview

As shown in Figure 2, the process begins with an interactive dialogue between the user and the chatbot, where the user submits a bug report and the chatbot engages with follow-up questions until sufficient detail is collected. After this point, the agents attempt to enhance the report to ensure clarity and completeness. Once the enhancement is completed, the agents repeatedly try to reproduce the bug. If reproduction is unsuccessful after a specified threshold of iterations, the task is escalated to customer support for manual reproduction.

Following reproduction, the agents classify the bug and then execute the bug–feature tracer to determine which feature the bug is related to. Once this tracing is complete, the agents evaluate the validity of the bug. If the bug is deemed invalid, the agents attempt to resolve it through a no-code fix. This resolution is overseen by customer support to ensure accountability. If verification fails repeatedly and exceeds the predefined threshold, customer support provides a manual no-code fix. Once either the agent-based or manual fix is confirmed, the user is notified and asked to verify the resolution. If the user confirms the fix, the process ends; if not, the lifecycle restarts from the beginning.

If the bug is determined to be valid, the PM or team lead decides whether it should be fixed. If the decision is negative, the user is notified, and the lifecycle ends. If the bug should be fixed, the agents

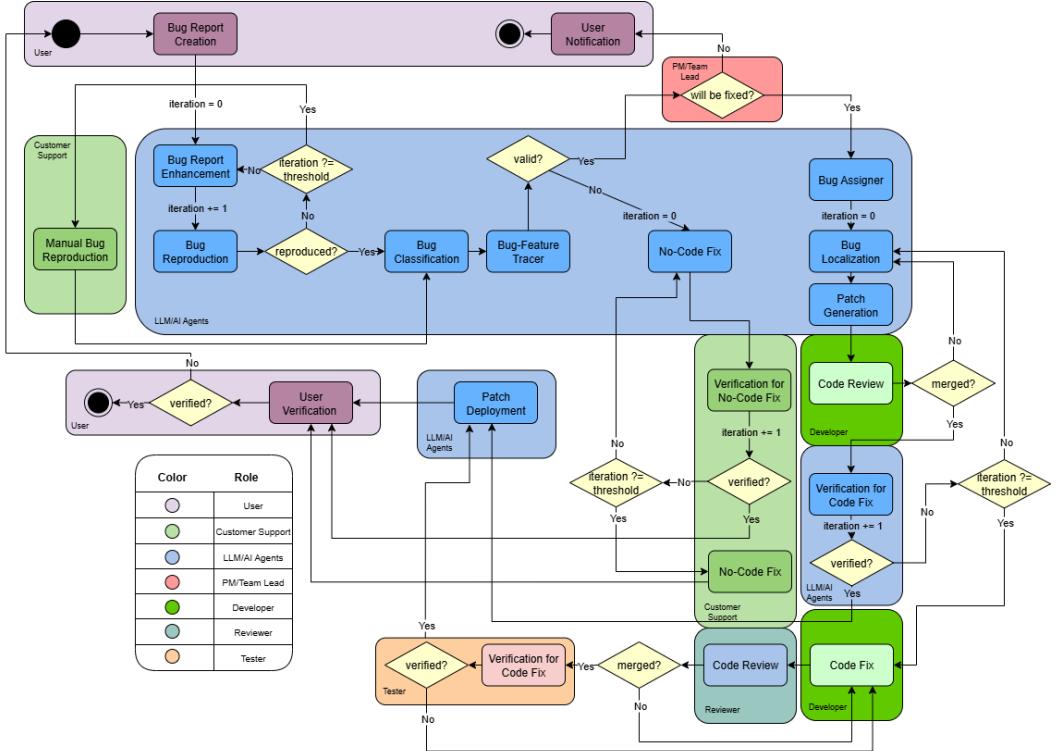


Fig. 2. Overview of Proposed Bug Tracking Framework Workflow

assign it to a developer, with the assignment reviewed by the team lead to ensure accountability. Even though agents may generate patches, human oversight ensures that a responsible developer is always associated with the bug to preserve accountability across the project.

Once assigned, the agents localize the bug and generate a candidate patch. The developer then reviews this patch. If the developer decides not to merge, the agents repeat the localization and patch generation process until a valid solution is produced or a predefined threshold is reached. When the developer accepts the patch, the verification phase is carried out by LLM/AI agents, which attempt to verify the fix within a specified threshold of iterations. If verification by the agent fails, the responsibility shifts back to the developer, who manually fixes the bug. This manual fix is then reviewed by another developer acting as a reviewer. If the reviewer rejects the manual patch, the developer revises it until approval is achieved. The cycle resumes with the tester once the reviewer merges the patch. If the agents cannot again verify the bug within the threshold, the developer continues revising until successful verification is achieved.

When agent-based verification (or subsequent developer revisions) confirms the fix, the patch is deployed, and the user is once more asked for final verification. If the user accepts the fix, the lifecycle is completed. If the user rejects it, the process restarts from the beginning, ensuring continuous accountability, resolution, and user satisfaction. The details of each phase in this lifecycle are elaborated in the following subsections, where we describe the design, methodology, and role of agents at every stage of the process.

**3.1.1 Bug Report Creation.** In modern software projects, bug reports remain the primary channel through which users communicate problems to developers. These reports are usually submitted through issue tracking systems such as Bugzilla, Jira, or GitHub Issues, where users manually fill out forms that include fields like a summary, description, S2R, and sometimes severity or priority levels. Empirical studies of large ecosystems such as Apache, Eclipse, and Mozilla show that this structured but largely manual approach to bug reporting has become standard practice in the industry [158]. More recent surveys confirm that bug reports today generally consist of textual descriptions, optional attachments such as screenshots, and structured fields that are later consumed by downstream tasks such as triaging or classification [89].

At the same time, the research community has begun to investigate new ways to facilitate bug report creation by reducing the burden on reporters and capturing more useful information from the outset. Several studies have highlighted that critical elements such as observed behavior (OB), expected behavior (EB), and S2R are often missing or only partially provided in bug reports, particularly for web applications [127]. To address these gaps, interactive systems have been proposed that actively guide users during the reporting process. For example, BugListener [109] demonstrated how informal conversations in collaborative live chats can be automatically transformed into structured bug reports, synthesizing OBs and EBs as well as S2R. Similarly, other research has shown that automatic follow-up questions can be selected when reports are incomplete, ensuring that reporters provide the information most useful for later reproduction [61].

Building on this line of work, chatbot-driven reporting has emerged as a promising paradigm. Systems like BURT [113] provide end-users with an interactive interface where a conversational agent guides them step by step, asking clarifying questions, suggesting graphical options, and providing instant feedback on whether their descriptions are clear and sufficient. A related study further demonstrated that such task-oriented dialogue systems can significantly improve the quality of bug reports compared to static template-based forms, especially when dealing with visually observable defects in mobile and GUI-based applications [114].

In our framework, we extend this trajectory by employing an LLM-powered chatbot as the entry point for bug report creation. Unlike static forms, our chatbot accepts natural language input from users and adaptively engages them with follow-up questions whenever essential details are missing. This direct interaction helps resolve the asynchronous nature of current bug reporting, where users often wait hours or days for feedback, by providing immediate responses and clarification in real time. For example, if a user reports, “the login page freezes after I click submit,” the chatbot may follow up by asking, “What did you expect to happen after clicking submit?” and receive the response, “I expected to be redirected to my account dashboard.” It can then request further context, such as the browser used or whether any error message appeared. At the same time, certain environmental details such as OS, app version, or device type can often be inferred automatically from metadata without needing to ask the user directly. By the end of this short exchange, the chatbot compiles a structured report that contains the OB (page freeze), EB (dashboard redirection), and key environmental details (browser, OS, error messages), ensuring that the report is both complete and minimally burdensome for the user. This ensures that the key components of a bug report are systematically captured during the initial interaction. By grounding bug report creation in a conversational process, we aim to both reduce the cognitive effort for end-users and increase the completeness and usefulness of the reports passed downstream to subsequent phases of our framework.

**3.1.2 Bug Report Enhancement.** In our proposed methodology, end users create bug reports from scratch, as detailed in Section 3.1.1, with the support of an LLM assistant. Despite this guidance, bug reports may still contain ambiguities or missing information because end users are often non-expert

reporters [113]. Therefore, after creation, bug reports are evaluated for completeness, clarity, and conciseness. Prior research has identified structural completeness, clarity, and the presence of core components as key dimensions for report quality [12]. Subsequent studies proposed automated techniques for detecting missing information, including incomplete S2R steps [18, 19, 112].

Recent studies have leveraged LLM capabilities to enhance bug report quality. LLM-driven approaches can semantically analyze bug reports and detect missing fields [92]. They can suggest enhancements for incomplete descriptions [16] or ambiguous content [39]. Critical information such as system state, error messages, and execution logs can be added by the agent [129]. The agent can also ensure S2R steps are complete [35]. Furthermore, LLMs maintain consistency with prior examples and best practices in bug reporting [111]. This process ensures that enhanced reports are actionable for developers [113].

In our methodology, the bug report enhancement process adopts this LLM-driven approach. The agent first analyzes the submitted report and evaluates its quality against criteria such as completeness, clarity, and conciseness that are defined by Bettenburg et al. [12]. Based on this assessment, the agent proposes enhancements, filling missing details or rephrasing ambiguous descriptions [35, 92]. Both the original and enhanced versions of the bug report are stored in the database, allowing developers or stakeholders to reference the original submission if necessary. For all downstream tasks in our proposed bug tracking workflow, such as bug reproduction, localization, and no-code fixes or patch generation, the enhanced version is used as input, as well as the original report, for developers' later references.

**3.1.3 Bug Reproduction.** In early systems, bug reproduction was manual: test engineers, customer support, or developers attempted to follow the S2R included in the report, often needing to contact users for clarification when the description was incomplete or ambiguous. Research gradually moved toward automation. Techniques emerged to extract reproduction steps from natural language descriptions [154] or to leverage runtime information such as logs, execution traces, or telemetry [126]. In mobile and GUI domains, specialized approaches replayed user reviews, event sequences, or monitored app interactions to recreate failures [84]. These works highlight how the community attempted to reduce reliance on manual effort, though success was often limited to narrow domains or specific application types.

With the rise of LLMs, bug reproduction has increasingly been reframed as a generative task. LLMs can read bug descriptions and produce candidate test cases or executable scenarios that explicitly trigger the reported failure, thereby supporting the reproduction of the underlying bug. LIBRO [66] demonstrated that LLMs are capable of generating test cases from natural language bug reports. Other studies integrated visual context: ReCDroid+ [156] and vision-based reproduction methods showed how screenshots and GUI interactions can be leveraged to systematically replay UI-intensive failures [128]. More recently, feedback-driven methods like ReBL [129] explored iterative prompting and adaptation, where an LLM interacts with execution feedback to refine its reproduction strategy over multiple rounds. BugCraft [148] extended this idea into the game domain, showing how iterative synthesis and refinement can be applied to highly interactive environments. Most recently, work at Google has shown that agentic BRT (Bug Reproduction Test) generation, where an LLM agent produces fail-to-pass tests that both reproduce and validate bugs, can significantly improve industrial-scale automated program repair by providing stronger debugging and validation signals [25].

Building on this trajectory, our methodology operationalizes bug reproduction as an iterative loop tightly coupled with bug report enhancement. Once a bug report is enhanced, the agents attempt automated reproduction in a controlled sandboxed or containerized environment, ensuring

determinism and isolation from external noise [21]. For GUI bugs, this involves simulating user interactions based on screenshots or videos [87, 155], while backend and API bugs may be reproduced by replaying logs or workloads reconstructed from user sessions [126]. If reproduction succeeds, the system generates an executable artifact that can be passed to verification and integrated into regression pipelines.

If reproduction fails, the system increments an iteration counter and loops back to the bug report enhancement phase. Here, LLM agents refine the S2R by reordering actions, adjusting parameters, adding missing environmental constraints, or even requesting specific artifacts such as logs or screenshots [37, 39, 65]. The refined report is then re-executed, and this loop continues until reproduction succeeds or a threshold is reached. At that point, the case escalates to customer support for manual handling.

This iterative loop transforms reproduction from a one-shot attempt into a self-correcting process, where each failure strengthens the next attempt. Bug reports thus become dynamic artifacts that evolve through agentic refinement until a reproducible scenario is achieved. By feeding these successful reproductions into regression test suites, our framework not only reduces TTR but also creates an expanding safety net to prevent regressions in future builds [92].

**3.1.4 Bug Classification.** Once a bug is successfully reproduced, the next step is classification. Traditional bug triaging typically requires substantial manual intervention to evaluate factors such as severity, impact, and priority. Practitioners look for cues in the bug report, such as affected features, system logs, and error messages, to gauge how urgently a fix is needed. This manual process can be time-consuming and prone to human error, as it often depends on individual judgment and expertise.

Beyond severity and priority, the classification may follow various taxonomies based on the bug's nature—e.g., functional, performance, UI, or security [34]. These categorizations help teams allocate appropriate resources (e.g., security experts for security bugs or UX designers for UI issues) and streamline the handoff process between different roles within an organization.

Recent research has explored the use of ML [72, 74] and LLMs [34, 70, 82] to automate bug classification by analyzing bug report text to infer severity, category, and potential root causes. Mashhadi et al. [93] show that using fine-tuned CodeBERT for bug severity prediction improves results by 29%-140% for several evaluation metrics, compared to classic ML prediction models. In addition, an LLM-based bug-fixing time prediction classifier [6] could be helpful while assigning priority and severity.

In our proposed framework, we predict the priority, severity, and type of the bug before checking the trace link using previously studied ML/LLM classifiers. Such AI-driven approaches can systematically process bug reports to provide near real-time classification, thereby decreasing TTR.

**3.1.5 Bug-Feature Traceability.** In the literature, several traceability link categories are available using different artifacts such as requirements [2, 49], software documentations [3, 40], test cases [41], and issues [91, 149]. ML models [41] and LLMs [2, 53] are being used to achieve different traceability tasks.

Building on these advances, our framework proposes to maintain bug–feature trace links, explicitly connecting each reported defect to the product feature it affects. The primary benefit of this form of traceability is the ability to contextualize and prioritize defects within the broader product architecture. By automatically mapping a bug to the specific feature it impacts, development teams gain a clearer understanding of the bug's scope and potential consequences. This connection supports more informed decision-making: project managers can accurately identify which features are most problematic, allocate resources where they are most needed, and ensure that critical issues affecting key functionality are addressed promptly.

In addition, bug–feature traceability creates a valuable historical record. Over time, this repository of links enables trend analysis, revealing features that are consistently error-prone and guiding long-term architectural improvements or targeted testing strategies. Such trace links also strengthen downstream activities such as release planning, regression testing, and impact analysis, since developers can quickly determine which features are likely to be affected by a change or a newly discovered defect.

Automating this process minimizes the risk of human error and overlooked relationships that commonly occur in manual triage. It also facilitates cross-team communication by providing a shared, up-to-date view of the relationship between bugs and features. Ultimately, maintaining accurate bug–feature trace links supports a more streamlined and data-driven defect resolution process, helping to reduce maintenance costs and improve overall product quality.

**3.1.6 Bug Validity Check.** After a bug has been successfully reproduced and classified, the agents evaluate its validity before proceeding further in the lifecycle. Not all reported issues correspond to genuine software defects; some may stem from misunderstandings of EB, incorrect configurations, or environment-specific constraints [120, 138]. The bug validity check ensures that only issues requiring a code-level fix are advanced for resolution, while invalid reports are categorized appropriately, thereby avoiding wasted development effort.

Early studies have demonstrated that analyzing S2R can effectively distinguish between valid and invalid bug reports [38]. Other works extended this by leveraging system logs and error messages to identify whether reports contained sufficient technical detail for validation [55, 77]. More recently, research has examined how noisy and incomplete logs in industrial contexts complicate this process and developed methods to handle such cases [76]. In parallel, approaches that exploit semantic and contextual information from bug descriptions have shown promise in improving classification and filtering accuracy [94].

Building on these studies, our proposed workflow employs an LLM agent to perform the validity check by analyzing S2R, logs, and error messages while also handling noise and ambiguity in real-world reports. The LLM agent can also use traditional ML models to make a decision about the bug report’s validity. To further strengthen its decision-making, the agent cross-references historical bug reports and project documentation in a retrieval-augmented generation (RAG) setting as in Dinç et al.’s study [32].

If the reported behavior corresponds to an intended feature or an expected system outcome, the agent classifies the bug report as invalid. Invalid bugs are then mapped to a structured taxonomy like user error, duplicate report, configuration error [123], and the workflow continues with the no-code fixes targeting such cases. As part of this process, the LLM agent also generates a natural-language explanation for why a report was labeled as invalid. This explanation can later be consumed by other agents in the workflow, such as those generating no-code fixes. Also, this explanation can be used and overwritten by the customer support staff while deciding about validity, as the customer support staff supervises this process. Finally, this explanation can also be provided to end users, thereby improving transparency and user trust.

If the bug is deemed valid, responsibility shifts to the PM, who decides whether the bug will be fixed. If the PM determines that the bug should not be fixed, the report is labeled as *Won’t Fix*, and the user is notified of the rationale behind this decision.

By incorporating an agentic bug validity check, our proposed bug tracking framework will effectively filter out false positives and ensure that only actionable bugs are advanced to PM and developers. This agentic validation mechanism would not only improve the precision of bug tracking but also contribute to more efficient use of engineering resources, minimize human labor, solve class imbalance problems that frequently occur in ML algorithms, and decrease TTR.

**3.1.7 Bug Assigner.** After the bug’s validity is checked, the next step is assignment. In our methodology, if the bug is not valid, it is still routed to the no-code fix stage handled by LLM agents, which is explained in the next subsection. At the same time, the bug is assigned to a customer support representative to ensure oversight and accountability, so that at least one person remains responsible for the bug until it is formally closed. In practice, there could be multiple customer support representatives available, but for simplicity, our current assumption is that there is only one, and the invalid bugs are consistently assigned to that individual. If the bug is valid, the PM or Team Lead first determines whether it should be fixed. For bugs approved for fixing, the bug assigner agents automatically recommend the most suitable developer, and these recommendations are then reviewed by the PM or Team Lead before the bug moves to the fixing stage.

The task of bug assignment has historically been studied under the umbrella of automated bug triage. Early research treated assignment as a text classification problem, using techniques such as TF-IDF [115] representations and Naive Bayes classifiers to route bugs to developers [27]. Semi-supervised approaches extended this line of work by leveraging unlabeled bug reports to improve classifier performance [145]. Large-scale empirical studies examined how these models perform in industrial contexts, showing both potential and practical challenges [30]. More advanced approaches modeled developer behavior through bug tossing graphs to reduce reassignment and misallocation [14]. Topic models were also employed to capture latent semantics in bug reports and better align them with developer expertise [141, 147]. Other frameworks explicitly considered developer interest and workload in the assignment process [10]. While these approaches significantly reduced the manual effort involved in bug triage, their reliance on shallow features and frequent retraining limited their scalability and adaptability.

With the advent of deep learning and LLMs, a new generation of approaches emerged. Transformer-based methods such as BERT [31] have been applied to bug triage, enabling richer semantic representations of bug reports and improving accuracy [81]. Ensemble approaches that combine multiple language models have further improved robustness and prediction performance [75]. Beyond software maintenance, similar ideas have been explored in incident management: COMET demonstrated that LLMs can provide accurate and interpretable assignment of cloud incidents at Microsoft, showing that LLMs can reliably map natural language reports to the right resolver [135].

Our methodology builds on these advancements by introducing AI-powered bug assigner agents that act as an integral part of the bug tracking system. Once the decision to fix has been made, the agents automatically identify the most appropriate developer based on semantic similarity to historical bug assignments, workload balancing, and alignment with project policies. Assignments are generated quickly and consistently, minimizing costly bug tossing and delays. Importantly, the PM or Team Lead remains in the loop as a reviewer, ensuring accountability and organizational oversight.

**3.1.8 Bug Handling with No-Code Fixes.** If a bug report is deemed invalid, it often requires no-code fixes. No-code fixes resolve such issues by making changes outside of the application’s source code, typically involving adjustments to configuration files, server settings, user permissions, or system-level parameters. In current bug tracking platforms, these fixes are usually proposed and applied by customer support staff rather than PMs or developers, since they often relate to usage errors, misconfigurations, or environment-specific issues rather than programming defects.

The proposed approach builds on a growing body of research in automated configuration troubleshooting and repair. Early works such as PeerPressure [130] leveraged statistical comparisons across systems to detect anomalous configuration states, while AutoBash [117] introduced speculative execution of configuration changes with rollback guarantees. More recent approaches, including ConfAid [8] and range-based fix generation [142], have shown that dynamic analysis and

constraint-based reasoning can effectively localize and repair misconfigurations. Recent studies also explore the use of LLMs for automated repair of container and cloud configuration errors [150], highlighting the increasing feasibility of applying LLM-driven agents to this domain.

In our proposed workflow, no-code fixes are automatically recommended by the LLM agent. The agent analyzes the S2R, logs, and error messages provided in the bug report, and cross-references them with historical bug data and project documentation in a RAG setting. For invalid bugs, the agent proposes minimal, targeted adjustments such as correcting environment variables, updating database connection strings, revising access permissions, or tuning server timeout values. In this HIL setting, customer support staff act as supervisors for this step, reviewing the no-code fixes and modifying necessary parts.

To ensure that proposed fixes do not inadvertently introduce new defects, our bug tracking system employs a generate-and-validate process in an HIL setting. First, the LLM agent localizes the relevant configuration options associated with the reported failure. Next, it generates one or more candidate adjustments, informed by both learned patterns and historical resolution strategies. The effectiveness of these adjustments is assessed using automated regression tests, integration checks, or environment-specific predicates. If a candidate fix resolves the bug without introducing side effects, it is directed to the end user under the supervision of the customer support staff.

**3.1.9 Bug Localization.** Once a PM approves a bug for fixing and confirms the assignment, the process of bug localization begins. Historically, this has been a challenging task, as developers must manually sift through vast and complex codebases to find the exact line of code responsible for an issue [43]. Traditional bug localization techniques, such as Information Retrieval-Based Fault Localization [140] and Spectrum-Based Fault Localization [136], have been effective, but they are often complemented by other methods. Slicing-based fault localization [137] narrows down the search space by identifying relevant parts of the code that could influence the program's behavior, while Mutation-based fault localization [42] generates a set of mutants (tiny, seeded bugs) to see if they can be killed by the failing test cases, thus helping to pinpoint the real bug. Still, these methods often rely on statistical analysis of test coverage rather than a deep understanding of the code's semantic meaning.

The recent integration of LLMs has introduced a new paradigm, significantly enhancing debugging efficiency by going beyond traditional methods. Researchers have proposed various frameworks and systems to leverage LLMs for localization [33, 63, 85, 146]. For instance, the FlexFL framework [144] introduces a two-stage approach. The first stage uses traditional fault localization techniques to narrow down potential bug locations, and the second stage uses an LLM-based agent to perform a deeper analysis of the reduced search space. Similarly, SOAPFL [105] formalizes the bug localization process into a Standard Operating Procedure (SOP) that mimics a human developer's workflow, comprising comprehension, navigation, and confirmation steps. These studies showcase how LLMs can directly understand the semantic meaning of the code itself, enabling a more intuitive and accurate approach to finding the root cause.

Our system will use LLMs to analyze not only source code but also execution traces, system logs, and stack traces to determine where a failure originates. By leveraging historical debugging data and dependency graphs, the system will pinpoint the most likely areas of failure and reduce the search space for developers. This automation ensures that once a bug is approved for fixing, developers receive clear, context-aware insights into its root cause, significantly improving efficiency in the localization process.

**3.1.10 Patch Generation.** Once a bug has been localized, developers receive AI-assisted recommendations for potential fixes. While a bug's root cause may be understood, the actual process of changing the code is not trivial, as it can introduce new issues or ripple effects in other parts

of the system. Historically, automated program repair (APR) has sought to address this by using techniques such as generate-and-validate approaches. Early methods like GenProg [80] showed promise but were often limited by the randomness of their mutation operations, which could lead to nonsensical or unmaintainable patches. Other approaches, such as Prophet [88], improved upon this by learning a probabilistic model from a dataset of human-written patches to rank potential fixes. Despite these advances, these methods often struggled to generalize and faced challenges in understanding the broader semantic context of a bug.

The recent advancements in AI-driven patch generation have revolutionized this part of the bug-fixing process, and we would utilize existing studies to establish our semi-automated bug-tracking system. This is a well-studied field, with a growing body of research demonstrating how LLMs can automatically generate code fixes for a wide range of bugs [60, 64, 132, 139].

In our proposed framework, the LLM generates multiple candidate patches, each of which is reviewed by a developer or designated reviewer. If a patch is approved during this review, it is merged; otherwise, the generation–verification cycle is repeated. If the number of unsuccessful cycles goes beyond the set threshold, the developer manually creates a fix.

By using this approach, instead of manually sifting through the code to create a patch, developers can review and refine AI-generated suggestions, freeing them to focus on more complex, creative tasks. By minimizing human error and proactively suggesting optimal fixes, the system ensures that the final product is more robust and secure.

**3.1.11 Patch Verification.** In the patch verification step, our system assesses the correctness of generated patches and iteratively refines them to ensure reliability and semantic correctness. Foundational work in APR highlighted the importance of rigorous verification to move candidate patches from plausibility to practical adoption [104, 143].

Recent studies have explored leveraging LLMs for patch generation and validation as well as verification. LLM-driven approaches can generate test cases to verify candidate patches [83], detect semantic deviations [133], and iteratively refine patches based on verification feedback [79]. These methods demonstrate the potential of LLMs to improve patch correctness, coverage, and production readiness.

Building on these insights, our methodology integrates an LLM agent into the patch verification workflow. After a patch is generated, the agent validates it against both developer-provided and automatically synthesized oracles, utilizing artifacts generated in reproduction as detailed in Section 3.1.3. Regression tests are executed automatically to confirm that the bug is resolved without introducing new failures. In this HIL setting, test engineers supervise the verification process, reviewing the results and ensuring that candidate patches meet quality standards. Until a predefined number of iterations threshold, our proposed workflow goes back to bug localization and generates new patches in cases of verification or regression testing failures. This approach bridges the gap between APR and practical patch adoption, moving beyond syntactic plausibility toward semantically correct, production-ready fixes. If the agent cannot verify within a specified number of iterations, the verification task would be delegated to the test engineer.

**3.1.12 Patch Deployment.** Patch deployment in contemporary software organizations is typically realized through CI/CD pipelines, supported by toolchains that automate the path from code to production. In practice, once a patch is verified and merged, CI/CD platforms such as Jenkins<sup>25</sup>, GitHub Actions<sup>26</sup>, or GitLab<sup>27</sup> CI trigger build processes, package the code, run integration and

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<sup>25</sup><https://www.jenkins.io/>

<sup>26</sup><https://github.com/features/actions>

<sup>27</sup><https://about.gitlab.com/>

regression tests, and then promote the artifacts to staging or pre-production environments. From there, deployment into production may follow patterns such as blue-green deployments or canary releases, which reduce risk by gradually exposing the patch to subsets of users before a full rollout. Industry studies highlight that these practices significantly accelerate release frequency and improve reliability. For instance, case evidence from Paddy Power's adoption of continuous delivery demonstrates that releases shifted from a few times per year to weekly or even daily, with deployment becoming a single-button operation instead of a multi-day manual task, leading to dramatic improvements in productivity, quality, and customer satisfaction [23]. Likewise, a multiple-case study of Finnish software-intensive companies shows that organizations with more automated toolchains, especially those minimizing manual steps, are able to deploy faster and more reliably, while gaps in automation—such as missing performance testing or acceptance testing—directly slow down the delivery cycle [97].

Despite this progress, patch deployment still remains largely a DevOps responsibility, with human operators accountable for execution and rollback in case of failure. LLMs have not yet been used to autonomously perform deployment, but they open new opportunities to augment the process. LLMs can generate deployment scripts, infrastructure-as-code specifications, and container orchestration files, reducing the manual effort required to configure environments. They can also enhance monitoring by analyzing telemetry and log data post-deployment, quickly surfacing anomalies or regressions that would otherwise require manual inspection. Furthermore, LLMs could assist in adaptive rollout strategies by reasoning over user feedback and operational metrics to recommend accelerating, pausing, or rolling back deployments. However, accountability cannot be transferred to an automated agent, so deployment remains a hybrid process where LLMs act as copilots rather than autonomous actors.

Our methodology builds directly on these insights. When the tester or LLM/AI agent verifies the bug, the deployment itself continues to be executed by the CI/CD infrastructure and operations teams, but the LLM acts as an intelligent assistant across the deployment lifecycle. It prepares deployment descriptors alongside generated patches, reasons about potential risks before rollout, and provides continuous monitoring support after deployment. In doing so, it reduces manual effort, accelerates the transition from patch generation to user verification, and integrates deployment more tightly into an LLM-augmented bug tracking lifecycle. Following successful deployment, the system immediately involves the end user in the final verification step. The user receives a summary of the deployed fix and is prompted to confirm whether the issue has been resolved satisfactorily. If the user accepts, the bug is closed and marked as resolved; if not, the process loops back to the reporting stage with enriched details, ensuring continuous accountability and refinement until the user is satisfied.

### 3.2 Architecture of the Proposed Bug Tracking System

Our proposed bug tracking system employs a multi-LLM agent design in which specialized LLM agents are assigned to discrete steps in bug tracking. Rather than relying on a single monolithic model to handle all tasks, each agent is optimized and prompted for a particular subtask and consumes a curated context tailored to that role, such as historical bug fixes for localization and no-code fix suggestions. This decomposition enables each agent to use prompts and toolchains best suited to its objective, retain compact, task-relevant context for efficiency, and produce more focused, explainable outputs that can be validated in an HIL setting. Agents communicate via a lightweight coordination layer so that the outputs of upstream agents can be used by downstream agents. For example, the enhanced bug report becomes the canonical input for downstream agents like bug localization and patch-generation agents. Throughout the workflow, HIL supervisors (customer support staff, test engineers, PMs, or developers) oversee critical handoffs and validations.

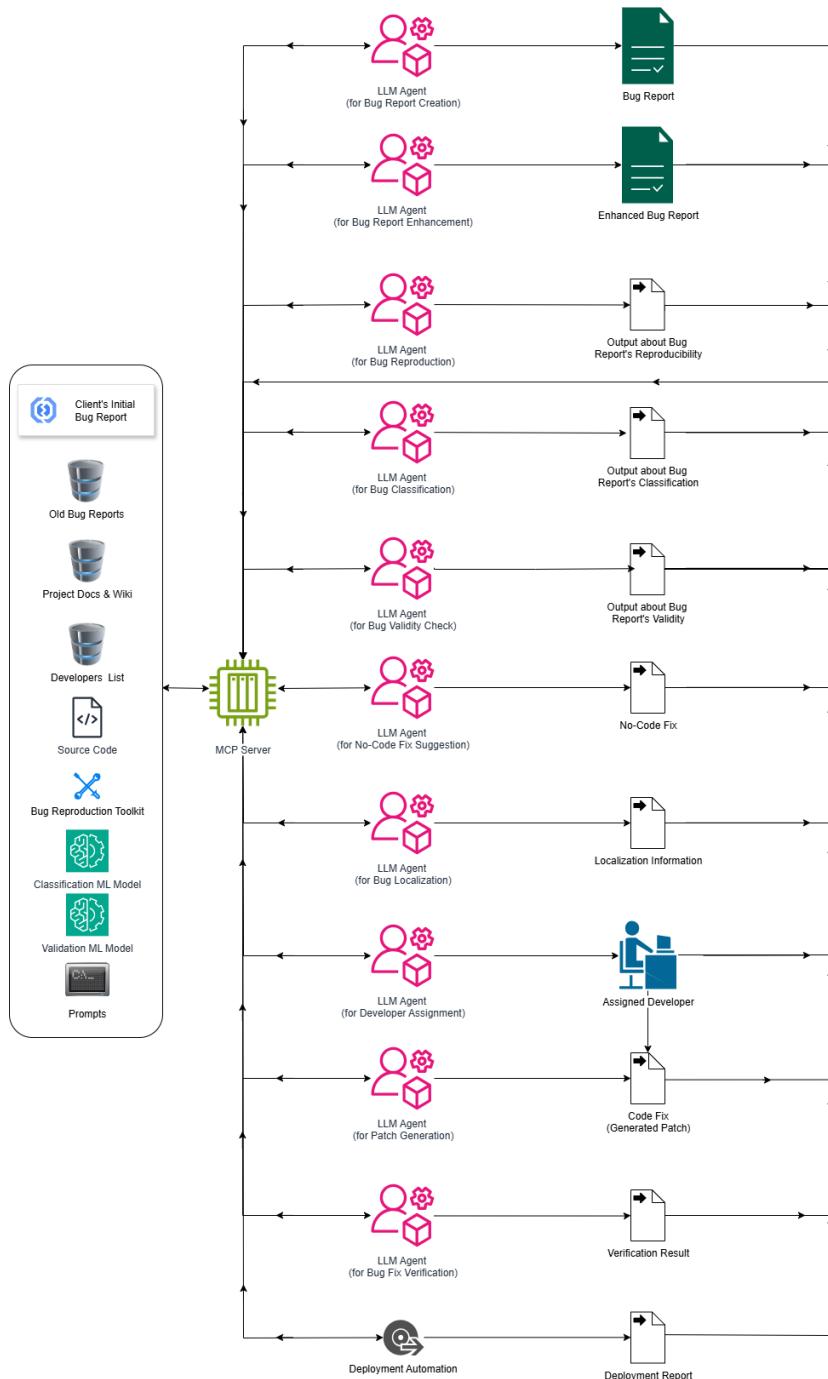


Fig. 3. Architecture of Proposed Bug Tracking Framework

While managing this complex system, which contains multiple data sources, toolkits, and multiple agents, we adopt the Model Context Protocol (MCP) [71] pattern. A dedicated MCP server acts as a broker and context store, exposing interfaces for prompt templates, cached retrieval vectors for RAG, historical artifacts such as old bug reports, project docs and wiki, developer lists, and source code, and tool integrations like the reproduction toolkit and ML models. The MCP centralizes agent registration, versioning, and policy enforcement while enabling agents to remain lightweight and interchangeable.

Figure 3 visualizes this architecture. On the left, persistent knowledge sources and tooling are shown (from the client's initial bug report to prompt libraries). The MCP server in the middle mediates access to these resources and hosts the coordination logic. To the right, there is a sequence of LLM agents; each row corresponds to one agent and its primary artifact, for example, LLM Agent for Bug Report Creation and Bug Report. Arrows indicate data flow: the initial report and auxiliary resources are read by the creation agent, the enhanced report is produced and sent to the MCP server and stored for downstream agents, and intermediate outputs like classification and validation results are stored for consumption by later stages. At the bottom, a deployment automation tool receives a verification result and produces a deployment report, closing the pipeline. We removed the MCP clients that exist in each MCP connection for the sake of simplicity from Figure 3. The diagram intentionally separates agents from resources and shows MCP as the single coordination and integration point, highlighting the auditability and reproducibility of every step.

In summary, the architecture provides a structured way to operationalize multiple LLM agents within a bug tracking system. By combining agent specialization with a central MCP for orchestration, we gain modularity, reproducibility, and governance. Agents can be updated, rolled back, or replaced independently; provenance for every recommendation is recorded; and HIL checkpoints are enforced where human judgment is required. Remaining system-level challenges include ensuring consistency of shared state across agents, managing prompt and model drift, verifying agent outputs at scale, and enforcing security and privacy policies. Addressing these will be key in future work to make multi-LLM bug tracking systems robust and production-ready.

### 3.3 Roles and Responsibilities of Each Stakeholder

Since we propose a new workflow for bug tracking, which integrates LLMs, the traditional roles and responsibilities of stakeholders participating in bug tracking are subject to change. This is because, with this new HIL paradigm, the workload shifts from being heavily dependent on manual effort toward a more balanced model, where LLMs perform core tasks under human supervision and guidance. Table 2 provides a summary of the evolving responsibilities, followed by a detailed explanation of each role transformation.

**End User:** In traditional settings, end users manually report bugs through email, ticketing systems, or predefined templates. They later confirm whether the fix resolves the problem or report if parts of the solution remain incomplete. In the proposed workflow, end users interact with an LLM-powered chatbot interface to report bugs. The LLM agent guides them by asking clarifying questions and ensuring that all required information is collected at the time of submission. End users are also notified about fixes through their preferred communication channel.

**Customer Support:** In the traditional bug tracking process, customer support staff receive bug reports and classify them as valid or invalid. They manually attempt to reproduce the bug using the provided S2R. If a bug is invalid, they may propose a no-code fix. They also act as intermediaries, communicating with both developers and end users regarding validity, status, and missing details. In the proposed workflow, customer support primarily acts as supervisors within the HIL workflow. Automated modules validate bug reports, attempt reproduction using provided S2R, and even propose no-code fixes when applicable. LLM agents communicate with end users about the process

and status, while human staff oversee these activities, intervening when the automation fails or produces ambiguous results. Customer support staff also acts as testers for no-code fixes suggested by LLM agents, by executing tests for no-code fixes.

Table 2. Transformation of Roles and Responsibilities of Stakeholders From Current Bug Tracking Workflow to Proposed Workflow

Role	Before	Proposed
End-User	Manually reports bugs and confirms fixes.	Uses a chatbot to report bugs and gets instant replies. LLM agents enhance already created bug reports.
Customer Support	Manually classifies, validates, and reproduces bugs. Communicates with developers and end users.	Supervises LLM agents in the HIL system. LLM agents automate bug validity check, classification, reproduction, and no-code fixes.
PM/Team Lead	Manually decides on if bug fixes happen, priority, and deadlines. Assigns bugs to developers.	Decides on bug fixes and deadlines. Reviews bot-assigned priorities and developer assignments.
Developer	Manually locates, reproduces, and fixes bugs.	Reviews and modifies code fixes suggested by LLM agents. LLM agents automate bug reproduction and localization.
Reviewer	Manually reviews and approves/rejects code changes.	Reviews the bug fixes if code is generated by the developer. If code is generated by the agent, the reviewer has no responsibility.
Tester	Manually writes and executes test cases. Verifies all fixes.	Supervises verification step in a HIL setup.
Ops Team	Manually deploys patches and monitors the production environment.	Focuses on infrastructure and CI/CD pipelines due to automated deployment and testing.

**Project Manager/Team Lead:** In traditional workflows, PMs decide whether a bug should be fixed, assign it to developers, prioritize its urgency, set deadlines, and track progress. They oversee the overall bug resolution process. In the proposed workflow, PMs retain strategic decision-making power, such as determining whether a bug should be fixed and setting deadlines for the subsequent steps in the bug tracking process. However, they now supervise agent-generated recommendations for priority and developer assignment, ensuring alignment with project goals. Thus, their role shifts toward overseeing and validating an LLM-assisted decision-making process.

**Developer:** In the current settings, developers manually localize and reproduce assigned bugs. After that, they implement code fixes. In the proposed workflow, developers act as supervisors in the HIL patch generation step. LLM agents handle bug reproduction and localization, and suggest code patches. Developers review, refine, and approve these changes, ensuring correctness and maintainability. They remain ultimately responsible for code quality.

**Reviewer:** Traditionally, reviewers manually review code changes, provide feedback, and approve or reject them based on quality standards. In the proposed workflow, reviewers continue to evaluate changes authored by developers. If an LLM generates a patch, the review is done by developers, so the workload of the reviewers decreases.

**Tester:** In the current workflow, testers manually create and execute test cases to verify code fixes. In the proposed workflow, testers act as supervisors in the HIL testing step. Test agents generate test suites, execute them, and verify both code fixes. Testers oversee this process, review generated test cases, and add or refine tests that exceed the LLMs' current capabilities. Their role shifts from execution to validation and augmentation, effectively becoming "Test Reviewers."

**Ops Team:** In the current bug tracking setup, the operations team manually deploys patches after verification and monitors the production environment. In the proposed workflow, the ops team's role becomes supervising LLM agents that take care of the ops team's tasks. LLM agents develop CI/CD pipelines and maintain them, while the ops team supervises and makes necessary modifications.

## 4 Discussion

This section critically discusses the implications of the proposed system, exploring its potential impact and the directions for future research in this field. Section 4.1 outlines major challenges and risks that must be addressed, ranging from technical hurdles like cascading errors and limited generalization to broader concerns regarding accountability and economic costs. In Section 4.2, the discussion turns to the practical implications for practitioners, detailing how the system's modularity, HIL design, and toolchain integration can be leveraged to transform software development workflows. Section 4.3 concludes the section by examining the implications for researchers, identifying a new landscape of research questions concerning task ordering, human oversight, and the evaluation of complex agent-based systems.

### 4.1 Future Challenges and Risks

As our proposed AI-driven bug tracking system relies on multiple automated steps powered by LLMs, several challenges and risks must be addressed to ensure its effectiveness and reliability. This section outlines key challenges that need further research and risks that could impact the system's performance.

**4.1.1 Accumulated Errors Due to Multi-Step LLM Dependency.** One of the primary risks in our approach is that multiple stages of the bug lifecycle, such as reporting, reproduction, localization, and patch generation, depend on LLMs, each of which has inherent limitations in accuracy. Since each step builds upon the output of the previous step, poor performance may propagate and amplify, similar to earlier studies [62]. This cascading effect could significantly reduce the final accuracy of bug resolution.

**4.1.2 Accountability Issue.** While LLMs can streamline bug tracking tasks from report generation and prioritization to suggesting potential fixes, they also introduce a significant accountability gap absent in traditional systems. The root of this problem lies in the "black-box" nature of LLM decision-making. Because the rationale behind an LLM's outputs is typically opaque, it is often unclear who or what should be held responsible when its recommendations lead to errors. This ambiguity complicates efforts to trace decisions back to a specific cause or actor and undermines the ability to conduct meaningful post-mortems. To address this problem, our approach incorporates a HIL design that explicitly assigns accountability to designated human reviewers, ensuring that final decisions can be audited and responsibility clearly established.

**4.1.3 Bias and Inaccuracy in LLM Predictions.** LLMs and ML models are trained on large-scale datasets that can contain biases or knowledge gaps, leading to misclassification of bugs, misleading explanations, or incorrect fixes caused by various factors such as code generation mistakes [24]. In specialized software domains, where data is scarce or domain knowledge is highly specific, LLMs

may struggle to provide accurate results. The challenge lies in determining the extent of these biases and inaccuracies and understanding how they affect different stages of bug tracking and resolution.

**4.1.4 Limited Generalization Across Different Software Projects.** A major future challenge in AI-driven bug tracking is ensuring that models generalize well across diverse software ecosystems. The effectiveness of an LLM-based bug tracking system may vary significantly depending on the programming languages, frameworks, and architectures involved. A model trained on one software type may struggle when applied to another, leading to inconsistencies in bug resolution accuracy. Future research must explore how to improve adaptability across different software contexts and what factors influence the performance of LLMs in varied environments.

**4.1.5 Evaluation.** Evaluating AI Agents is inherently complex [151]. Unlike traditional systems, where well-defined metrics such as accuracy or precision can be applied against a fixed gold standard, an agent-based workflow introduces fluidity that resists simple benchmarking. Many of the tasks performed by the agents lack a clear reference output, making it difficult to establish what constitutes a “correct” answer [67].

This problem has been widely recognized in the literature on agent evaluation. For instance, benchmarks for AI agents are often fragile, non-standardized, and overfitted to narrow test cases, which prevents them from reflecting real-world utility [67]. Similarly, surveys of LLM-based agents in software engineering stress that many agent tasks are inherently open-ended and multi-modal, making them difficult to evaluate using traditional gold-standard datasets [134]. The AgentBench [86] framework echoes this by highlighting that evaluating agents requires interactive, multi-turn, open-ended environments rather than static correctness checks.

Bug report enhancement exemplifies this challenge clearly. When an agent rewrites or augments a bug report, there is no canonical “ground truth” version of an enhanced report. Multiple plausible enhancements may exist, each potentially useful in practice. In such one-to-many generation tasks, conventional evaluation techniques such as BLEU or ROUGE fail because they assume a single correct output. Indeed, research in text simplification has shown that BLEU often misaligns with human judgments when multiple valid outputs exist, penalizing useful simplifications [118].

Bug assignment faces related challenges. Historical assignments could be used as training or evaluation data, but they often contain errors, misallocations, or excessive bug tossing. Using them as a gold standard risks reinforcing suboptimal practices. Moreover, our methodology deliberately differs from past approaches by assigning even invalid bugs to ensure accountability. This introduces a structural misalignment between our workflow and existing datasets: most publicly available datasets focus only on valid bug reports and downstream tasks such as localization or fixing, but they do not include cases of invalid bugs, no-code fixes, or iterative chatbot–user interactions. As a result, these datasets cannot fully capture the scope of our framework, which models the entire bug lifecycle end-to-end [134].

Another important difficulty lies in determining when reproduction or verification has truly failed. In traditional settings, failure is explicit, for instance, when a test case crashes or produces an incorrect output. In agent-based workflows, however, the situation is less clear. An agent may execute a sequence that does not reproduce the bug, but it is ambiguous whether this is because the reproduction was genuinely unsuccessful, because the inputs or environment variables were incomplete, or because the verification criteria were too strict. Similarly, verification may report a fix as successful while subtle side effects or untested conditions still exist. This ambiguity means that even deciding whether an iteration has failed becomes a challenge in itself, complicating both system design and evaluation.

These difficulties highlight a broader methodological gap in evaluating agent-based systems. Unlike deterministic algorithms, agents operate iteratively, refine their outputs, and adapt based on feedback. The quality of such systems cannot be measured only by whether the first output matches a historical reference. Instead, evaluation must consider whether the agent converges toward a useful outcome within practical limits of time and effort. As the literature emphasizes, reproducibility, process-based metrics, and HIL assessments are essential to capturing agent effectiveness [67, 86].

**4.1.6 Challenges in Dataset Availability and Reliability.** A significant challenge in advancing automated bug tracking systems is the scarcity of high-quality datasets that comprehensively capture real-world bug lifecycles. To reliably test the outcomes of such a system, there is a fundamental need for trusted data sources and benchmarks that can serve as a standard for verifying results. However, publicly available datasets are often incomplete or fragmented, while proprietary systems remain inaccessible due to confidentiality constraints.

Lack of datasets and benchmarks for evaluating bug tracking systems limits quantitative analysis of results, which can reduce reliability.

**4.1.7 Privacy Challenges of LLM-Powered Agents.** Integrating LLM-powered agents into bug tracking pipelines introduces significant privacy risks. Because these agents process user-submitted bug reports, execution logs, screenshots, and potentially sensitive contextual data, they create new attack surfaces for privacy leakage.

One challenge lies in memory extraction, where adversaries can design prompts to force agents to reveal stored or historical user information. Studies have shown that private memory contents in agent systems can be exfiltrated through black-box interactions, raising concerns about retaining sensitive bug data [125].

A second risk comes from tool-augmented agents, which interact with external systems such as file repositories or CI/CD pipelines. These integrations expand the attack surface, as malicious prompts or poisoned inputs can trick agents into exposing private logs or configuration data [54].

Privacy leakage is also possible through interface manipulation. For example, LLM-powered GUI agents have been shown to be vulnerable to fine-print injection, where invisible or low-salience instructions are embedded in user interfaces, leading the agent to execute unintended actions that compromise sensitive data [22].

Finally, the general opacity of agent behavior makes privacy risks harder to detect. Since agents continuously adapt their responses based on memory and prompts, unintentional disclosure of private bug reports or logs may go unnoticed until after data has been leaked. This unpredictability means that privacy risks are not isolated to adversarial cases but may also arise during normal operations [153].

**4.1.8 Economic Implications and Hidden Costs.** Beyond the immediate technical and ethical challenges, the adoption of AI-powered bug tracking systems presents a complex set of economic considerations that go far beyond simple licensing fees. While initial cost-benefit analyses might focus on the efficiency gains from automation, they often fail to account for the substantial hidden costs. These include the financial overhead of API calls, which can escalate unexpectedly with increased usage, as well as the significant infrastructure and computational costs for organizations choosing to host and fine-tune models internally. The cost of integrating these new systems with existing legacy tools and workflows can also be a major expense, requiring extensive development and testing.

## 4.2 Implications for Practitioners

**4.2.1 Adapting to Diverse Project Structures.** Our proposed bug-tracking system assumes a certain team structure with dedicated roles for PMs, developers, and other team members. However, we acknowledge that this may not align with every project. The organizational structure of software development teams can vary significantly across different projects and companies. It is important for practitioners to adapt our system to fit their specific needs.

For example, a small startup or open source project might not have a separate customer support team, with developers or the PM directly handling bug reports from users. In these cases, the system's bug reporting and triage processes would be streamlined to route information directly to the person who needs to act on it, bypassing a formal customer support or tester role. Similarly, in a small team, a developer might also serve as the tester, responsible for both writing code and creating test cases. The system should be flexible enough to accommodate this by allowing a single user to perform multiple functions, such as creating a bug report, localizing the bug, and implementing the fix.

By being aware of these potential differences, project teams can configure our system to reflect their actual workflow, ensuring that the benefits of automated bug localization and management are realized without forcing a rigid, and potentially inefficient, organizational model upon them. The system's strength lies in its ability to provide clear, context-aware insights, regardless of who is performing the different roles.

**4.2.2 Human-in-the-Loop System Training and Customization.** The successful adoption of our semi-automated bug tracking framework depends on its ability to integrate seamlessly with existing workflows. A key implication for practitioners is that this is not a "plug-and-play" solution; it is a HIL system that requires training and customization to achieve its full potential.

Our system's AI components, particularly the LLMs for bug localization and patch generation, can be fine-tuned on an organization's proprietary codebase and historical bug data. This process allows the models to learn project-specific nuances, coding conventions, and common bug patterns, making their suggestions more accurate and relevant. This is a crucial step that distinguishes a generic tool from a highly effective, tailored solution.

Beyond this technical fine-tuning, companies must create their own workflows to leverage the system's capabilities. For example, they should define clear rule sets that establish when a developer should accept an AI-generated fix versus when they should manually intervene. They must also establish feedback mechanisms for developers to provide input on the AI's suggestions, allowing the system to continuously learn and improve. Finally, companies should adapt the roles and responsibilities of their teams to maximize the benefits of automation; with the system handling routine tasks, developers can focus on high-level design and complex bugs, while testers can concentrate on validating the AI's fixes and exploring edge cases. By actively engaging in this HIL training and custom adoption, practitioners can ensure the system becomes an integrated and invaluable part of their development process, maximizing productivity and code quality.

**4.2.3 Modular System Architecture and Process Optimization.** The components of our bug-tracking system are designed with a modular architecture, meaning each part, from bug report enhancement and reproduction to fault localization and patch generation, can be run either independently or as part of a single, unified workflow. This is a critical implication for practitioners, as it allows for significant flexibility and process optimization based on a project's unique needs and constraints.

A project with a mature CI/CD pipeline, for example, might choose to run the entire system end-to-end, from the moment a bug is reported to the automated creation of a pull request with a suggested fix. In contrast, a team working on a legacy system or in a more manual environment

might opt to use only a single, specific component. They could, for instance, utilize the localization feature as a standalone tool to rapidly pinpoint the buggy code, then rely on human developers to manually create and test the fix. Similarly, a project with a dedicated QA team might choose to use the AI for bug report enhancement and reproduction, allowing testers to become more efficient without fully automating the fix generation step.

This modularity empowers development teams to choose a level of automation that suits their specific context, minimizing disruption while maximizing the system's benefits. By allowing projects to selectively adopt and integrate the most valuable components, our system becomes a highly adaptable tool that can be optimized for a wide range of software development processes.

**4.2.4 System Integration and Toolchain Adapters.** Successfully integrating such a bug-tracking toolchain into existing systems requires a strategic approach focused on building flexible adapters and connectors. These components serve as a crucial layer, allowing the system to communicate with and leverage existing development tools without requiring a complete overhaul of an organization's infrastructure. It is essential to develop these connectors for critical parts of the toolchain, such as VCSs like Git, which would allow the system to pull code and submit AI-generated patches as pull requests. Similarly, adapters for integrated development environments like Visual Studio Code<sup>28</sup> or IntelliJ<sup>29</sup> would provide developers with real-time AI recommendations and debugging insights directly within their coding environment. Furthermore, building connectors for CI/CD platforms such as Jenkins<sup>30</sup> or GitHub Actions is vital for automating the testing and validation of AI-generated fixes, ensuring that only verified code is merged. Finally, adapters for pre-existing bug-tracking systems like Jira would allow for the seamless import of bug reports, enabling a phased and non-disruptive adoption. This approach ensures that the new system acts as a powerful enhancement to the existing ecosystem, maximizing the return on the integration effort.

### 4.3 Implications for Researchers

The proposed framework highlights not only the technical contributions of automation but also opens a broad set of research opportunities. These implications arise at multiple levels, including the ordering of activities within the workflow, the role and positioning of human oversight, the scope of individual agent capabilities, and the ways in which domain- or bug-type specific factors shape system effectiveness. To structure these implications, we organize the discussion into several thematic areas, each representing a distinct line of inquiry for future research.

**4.3.1 Ordering of Activities.** Our methodology introduces automation across the bug lifecycle, but it also raises questions about how these activities should be sequenced. In our design, bug report enhancement precedes reproduction, which in turn is followed by classification, assignment, localization, and patch generation. While this ordering reflects common practice, it is not inherently optimal. Running classification before reproduction could help filter out low-priority reports and save computational resources, while prioritizing reproduction ensures that only actionable reports move downstream. These trade-offs point to a larger research opportunity: systematically studying how different pipeline orderings influence accuracy, efficiency, and TTR.

**4.3.2 Human Oversight and Accountability.** Automation cannot fully replace human judgment, and the positioning of HIL interventions is itself an open research question. For example, requiring project manager or team lead approval before assignment may ensure correctness but add delays, while placing oversight after assignment may reduce turnaround but risk misallocation. As another

<sup>28</sup><https://code.visualstudio.com/>

<sup>29</sup><https://www.jetbrains.com/idea/>

<sup>30</sup><https://www.jenkins.io/>

example, if a user submits a trivial or well-known bug, such as a minor UI inconsistency, a typo in the interface, or a frequently encountered issue that customer support is already familiar with, the agents may still attempt reproduction and classification. However, in such cases, customer support could immediately recognize the problem and provide a direct resolution without going through the entire automated pipeline. Similar trade-offs exist for reviewers, testers, and customer support. Studying these interactions will clarify how to balance automation with accountability in agent-based bug tracking systems.

**4.3.3 Agent Capabilities as Research Problems.** As illustrated in Figure 2, each capability represented in the workflow, such as bug report enhancement, reproduction, classification, localization, patch generation, and verification, can itself be viewed as a distinct research problem. Advances in natural language processing can refine bug report enhancement, program analysis techniques can strengthen localization, and test generation research can improve reproduction and verification. Researchers can therefore explore each of the boxes in Figure 2 as independent research topics, while also examining how these functions interoperate within an end-to-end framework that spans the entire bug tracking system.

**4.3.4 Domain-Specific Challenges.** The effectiveness of automated bug tracking will vary across domains. In delivery systems, bugs often occur immediately, making them straightforward to detect and reproduce. In contrast, interactive environments such as gaming may require long execution traces or rare conditions before a bug surfaces, complicating both reproduction and verification. These contrasts suggest that domain-specific adaptations of automation strategies are a promising research direction.

**4.3.5 Bug Type Differences.** Not all bug types are equal in terms of detection and automation. Crash bugs are often captured directly through logs or monitoring, making them easier to handle in automated workflows. Functional, performance, or usability bugs, however, are more nuanced and may require user modeling, advanced instrumentation, or long-term observation. Future research can investigate which automation strategies are most effective for which bug types, and how to design adaptive systems that tailor their methods accordingly.

Taken together, these considerations show that automated bug tracking systems should not be viewed as a single research challenge but rather as an ecosystem of interrelated problems. Investigating variations in task ordering, agent capabilities, human oversight, domain-specific challenges, and bug type detection can significantly advance our understanding of how intelligent bug tracking systems should be designed and deployed.

## 5 Conclusion

We presented a vision for a next-generation bug tracking framework that leverages LLMs in each possible step of bug tracking. By incorporating LLM-driven automation into report creation and enhancement, reproduction, classification, validation, localization, resolution, and verification, the proposed system aims to reduce developer workload and decrease TTR while improving the quality and efficiency of bug tracking and software maintenance in general.

The proposed system extends traditional bug tracking systems by employing conversational assistant agents to support users in creating bug reports, and later enhancing possibly overlooked fields in the bug report, automating the execution of reproduction steps, and improving the accuracy of bug classification and validation. Furthermore, the integration of no-code fix suggestions and LLM-assisted bug localization, followed by patches generated and deployed by LLM agents, provides the potential to decrease resolution times and optimize resource allocation.

Despite these potential benefits, several challenges remain. Key issues include ensuring the correctness and reliability of LLM-generated outputs, integrating the system with existing development workflows, and addressing complex, multi-step defects that require human judgment. Additionally, interpretability and transparency of LLM-driven decisions are critical considerations for adoption in industrial settings.

In conclusion, this work provides a conceptual framework for an adaptive, LLM-driven bug tracking ecosystem. Future research is required to operationalize these proposals, empirically evaluate their effectiveness in real-world software projects, and further refine the underlying models and methodologies.

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