# Vortex under Ripplet: An Empirical Study of RAG-enabled Applications

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Abstract—Large language models (LLMs) enhanced by retrieval-augmented generation (RAG) provide effective solutions in various application scenarios. However, developers face challenges in integrating RAG-enhanced LLMs into software systems, due to lack of interface specification, requirements from software context, and complicated system management. In this paper, we manually studied 100 open-source applications that incorporate RAG-enhanced LLMs, and their issue reports. We have found that more than 98% of applications contain multiple integration defects that harm software functionality, efficiency, and security. We have also generalized 19 defect patterns and proposed guidelines to tackle them. We hope this work could aid LLM-enabled software development and motivate future research.

Index Terms—component, formatting, style, styling, insert

#### I. INTRODUCTION

### A. Motivation

Large language models (LLMs) offer effective solutions for a spectrum of language-processing tasks. Retrieval-augmented generation (RAG) techniques further enhance their capability in concrete application scenarios, by providing relevant information from external data sources. Cloud services and various frameworks [1]–[6] also relieve developers from implementing and hosting their own LLM models and RAG solutions. Therefore, an increasing number of software systems have integrated RAG-enhanced LLMs to realize intelligence features, which this paper refers to as *LLM-enabled software*. Indeed, more than 36,000 open-source LLM-enabled software applications have been created on GitHub in recent 6 months, to solve a variety of real-world problems.

Cloud services and various frameworks have greatly eased developers' burden of incorporating RAG-enhanced LLMs. However, there still remain many challenges that must be addressed to build correct, efficient, and reliable LLM-enabled software. In fact, some non-expert developers may not even notice these failures, due to insufficient testing and lack of LLM and RAG knowledge. While much work has been conducted to improve LLM and RAG algorithms [7]–[9],

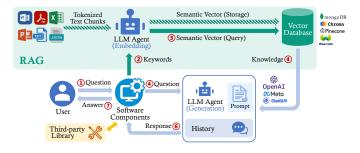


Fig. 1. Workflow of LLM-enabled software.

this paper focuses on the unique challenges raised by system integration of RAG-enhanced LLMs.

Challenge-1: Lacking interface specification. Performing cognitive and generation tasks, LLM agents and general AI components typically lack a specification detailing their behavior [10]. Given a particular input, LLM agents cannot specify whether it is able to provide a correct answer in an expected format.

In addition, as LLMs are instructed through text prompts and enhanced by RAG, it is also impractical to define the capability boundary of a certain LLM. Therefore, LLM-enabled software systems cannot formally describe the interface between the RAG-enabled LLM and the remaining software components. Thus, the developers have to tackle the under-specific interface and resolve potential failures.

Challenge-2: Requirements from software context. As a generative model, an RAG-enabled LLM inherently tends to provide different responses for the same question in multiple runs. While these responses may all seem feasible, not all of them will match the software context and trigger correct software behavior. For example, a user has different expected responses of "how to rename a file" when using a code editor and a system helper. Furthermore, conventional software components typically have strict format requirements, while the data-driven LLM agents support text of various formats.

Thus, the developers have to instruct the general-purpose LLMs to perform specific tasks within the software context and application scenario.

Challenge-3: Complicated system management. The LLM-enabled software contains multiple resource-intensive components that require system-level management to ensure performance, including LLM agents and vector databases that support RAG algorithms (see Figure 1). Even for software that adopts cloud services to reduce computation costs, they still need to allocate much memory for transferring and processing the intermediate results. Besides, LLMs face vulnerability problems and have become a weak link in system security after obtaining system privileges [11]–[13]. Thus, the developers have to carefully manage resources and protect security of the entire software system.

Prior work studies integrating general-purpose AI components [10], [14]–[16]. Other work focuses on enhancing LLM and RAG algorithms [7]–[9], [17], [18]. However, to the best of our knowledge, no prior work provides an empirical study detailing the integration problems of LLM-enabled software.

#### B. Contribution

To understand the integration problems in LLM-enabled software and provide guidance, we perform an empirical study of the latest version (as of May  $22^{nd}$ , 2024) of 100 GitHub applications that incorporate RAG-enhanced LLMs to tackle real-world problems, using various LLM and RAG frameworks. We manually studied more than 3,000 issue reports of these applications and summarized 19 defect patterns.

Our study find that integration defects are widespread and 98% of applications contain more than one type of defects. These defects lead to various problems, including unexpected fail-stops, incorrect software behavior, slow execution, unfriendly user interface, increased token cost, and secure vulnerability. They located in 4 major components of LLM-enabled software: (1) *LLM agent* that constructs prompt and generates LLM response; (2) *vector database* that supports RAG algorithms; (3) *software component* that interacts with the LLM agent and vector database; and (4) *system* that carries out the execution. Their root causes are all related to the challenges discussed above.

Our research reveals common defect patterns that exist in various applications, many of which could be relieved through simple code patches. Therefore, we also provide a systematic guide for developers to reveal and resolve these defects.

Overall, this paper presents the first in-depth study of integration failures in LLM-enabled software. It provides guidance to help prevent errors and improve software quality. We hope this work serves as a starting point for tackling this critical problem.

#### II. BACKGROUND

#### A. Retrieval-Augmented Generation

LLMs enable a wide range of cognitive features of the software, including conversation, document comprehension,



Fig. 2. A character simulation application RealChar [21].

and question-answering [19]. To further assist LLMs in resolving knowledge-intensive tasks, retrieval-augmented generation (RAG) techniques [7], [8] are proposed to provide external knowledge through prompt engineering. They equip LLMs with timely, trusted, and highly related knowledge that is unseen in its training procedure, without fine-tuning requirements. Therefore, LLM could be easily extended to various application scenarios and updated to the latest knowledge.

Several vector databases are proposed to manage external knowledge and provide RAG solutions, including MongoDB [20], ChromaDB [5], and Faiss [6].

As shown in Figure 1, the RAG algorithm contains two phases. In the storage phase, text is extracted from source files and sliced into multiple chunks, which is the knowledge entry. With the embedding module from an LLM, each knowledge entry is embedded into a semantic vector, which is a high-dimensional float vector that represents semantic features. These semantic vectors serve as the index of knowledge entries when stored in the vector database. In the query stage, the RAG algorithm embeds the query question using the same embedding module and retrieves relevant knowledge entries by the distance between semantic vectors. The retrieved knowledge then constructs the LLM context, simplifying the original knowledge-intensive task to a comprehension task.

## B. LLM-enabled Software

To further ease developers' burden, LangChain [3], LlamaIndex [4], and other frameworks provide unified interfaces for developers to integrate various LLMs and vector databases into software systems. This leads to the emergence of LLM-enabled software — more than 36,000 LLM-enabled software applications are created on GitHub in recent 6 months.

Figure 1 illustrates a common workflow of LLM-enabled software. Note that, some LLM-enabled software may have different workflows, but still follow a similar structure. Before the deployment, a *vector database* is initialized with carefully sliced text from various files. During the execution, a *software component* collects and converts user inputs. It then extracts key phrases to construct the query question and retrieve relevant knowledge from the vector database. An *LLM agent* then takes the retrieved knowledge and original user input to construct a prompt. It also manages the execution history and maintains the LLM context. Finally, the software component processes the LLM response and answers the user. Sometimes, the software component also invokes third-party libraries to assist data processing, user interaction, and other features.

Takes a character simulation application [21] that supports voice conversation as an example (Figure 2). It utilizes a vector database for storing character settings, and third-party libraries for conversion between voice and text. When the user asks about the character, the application retrieves the relevant information from vector databases to construct prompts. Therefore, the LLM agent could act as any character and correctly answer the question, as long as the vector database stores sufficient character-setting information. Of course, as we will discuss later, this application actually contains defects to be fixed.

#### III. STUDY METHODOLOGY

#### A. Application Selection

We collect a suite of 100 open-source LLM-enabled software applications for GitHub (all latest versions as of May  $22^{nd}$ , 2024). As GitHub contains many toy applications, we manually checked around 500 randomly selected open-source applications that incorporate both LLMs and vector databases for their intelligence features, to obtain these 100 non-trivial ones. We confirmed that they each targets a concrete real-world problem, tightly integrates LLMs and vector databases in their workflow (*i.e.* not a simple UI wrapper), and maintains an active user community.

Our application suite covers different programming languages, including Python(71%), TypeScript(24%), and others(5%). More than 90% applications utilize LangChain framework, due to its early release, while remaining create their own framework or other existing ones. Around 85% applications incorporate OpenAI services [1] as their LLM module, 10% use LLaMA [22], and the remaining use ChatGLM [23]. These applications incorporate various vector databases, including ChromaDB(45%), MongoDB(29%), Faiss(19%) and others(7%), through local deployment and cloud services. Due to the young age of RAG-enhanced LLM techniques, 40% applications are created within 12 months at the time of our study. Despite their young age, these applications are widely-used and actively updated. Half of the applications have received more than 135 stars, with the maximum value of 163,000. In recent 6 months, the developers of each application have made 500(374) commits on average(median).

In general, these applications support five major functionality categories, reflecting the common application scenarios of LLM and vector databases. Around 39% applications support context-based question-answering(QA), including document comprehension and knowledge search; 23% applications support task management, assisting users to achieve their goal; 19% applications serve as chat robots, keeping track of user-specific histories; 13% applications are in the form of central platforms, scheduling multiple correlated AI tasks; and the remaining 6% applications perform various text-related tasks, including automated fact-checking and plagiarism detection.

### B. Defect Pattern Identification

Since no prior work studies integration failures in LLMenabled applications. Therefore, we cannot rely on an existing list of defect patterns. Instead, our team, including LLM experts, carefully studied around 10,000 GitHub issue reports reported of the studied applications and obtained more than 3,000 bug-related ones. We manually confirm whether each of them is caused by software defects instead of end-user misuses: closed issues are confirmed by the developer's patch, and open issues are confirmed by issue reproduction through tests. We finally obtain 320 confirmed bug-related issues. We then generalize and cluster these issues, according to their root causes and impacts. For each cluster, we manually examine if there are similar defects in other applications and refine the clustering. We repeat this process for several rounds until converge to the findings in this paper.

In total, 19 defect patterns and 495 defects are identified. All issues and defects are examined by three of the authors, and their results are discussed and confirmed by all the coauthors.

#### C. Profiling Methodology

To understand how defects impact software performance, we profile the end-to-end latency of applications both before and after fixing. We use real-world data that reflect application scenarios, including text/voice queries and files of different formats, referring to application manuals and issue reports. By default, we run each test 10 times and report the average latency.

All experiments were conducted on the same machine, which has a 16-core Apple M3 Max CPU (4.05GHz), 32MB L2 Cache, 64GB RAM, 2TB SSD, and 1000Mbps network connection. Note that most applications perform LLM tasks through cloud services.

#### IV. IDENTIFIED INTEGRATION FAILURES

# A. Overview

Through empirical study, we identified 495 defects from 100 LLM-enabled applications and summarized 19 defect patterns, as listed in Table I. They are typically caused by developers' unsystematic prompt/query construction, misunderstanding of interface specification, unaware of software context, and lacking system management. They are widespread and harm software quality in various aspects: (1) functionality problems, including unexpected fail-stops, incorrect software behavior and unfriendly user interface; (2) efficiency problems, including slow execution and increased token cost; and (3) security problems.

We further explore the mechanism of these defects and divide LLM-enabled software into 4 major components that tightly work together: (1) *LLM agent* constructs prompt and generates LLM response; (2) *vector database* supports RAG algorithm and enhances the LLM agent; (3) *software component* is the remaining software that interacts with the first two components to perform certain tasks; and (4) *system* that manages resources and privileges to carry out the execution. Although we localize each defect pattern in a specific component, these patterns are actually related to the integration failure

 $\label{eq:TABLE} TABLE\ I$  Defects identified in LLM-enabled software.

Defect	Section	Location	Impact						Proportion of Problematic Apps	
			ST	IC	SL	UI	TK	IS	%	#/#
Unsystematic Prompt/Query Construction										
Unclear context in prompt	§IV-B1	LLM agent		<b>√</b>					23%	23/100
Improper similarity search	§IV-C4	vector database		<b>√</b>			✓		19%	19/100
Misunderstanding of Interface Specification										
Missing LLM input format validation	§IV-B4	LLM agent	<b>√</b>	<b>√</b>					23%	23/100
Incompatible LLM output format	§IV-B5	LLM agent	<b>√</b>	<b>√</b>		<b>√</b>			13%	13/100
Unnecessary LLM output	§IV-B6	LLM agent			<b>√</b>	<b>√</b>	<b>√</b>		23%	23/100
Exceeding LLM context limit	§IV-B7	LLM agent	<b>√</b>	<b>√</b>					31%	31/100
Knowledge misalignment	§IV-C1	vector database		<b>√</b>					28%	28/100
Improper text embedding	§IV-C3	vector database	<b>√</b>	<b>√</b>			<b>√</b>		34%	34/100
Conflict knowledge entries	§IV-C2	vector database	<b>√</b>	<b>√</b>				<b>√</b>	20%	20/100
Low-Frequency interactivity	§IV-D3	Software components	✓						90%	26/29
	Unawar	e of Software Context								
Lacking restrictions in prompt	§IV-B2	LLM agent		<b>√</b>					25%	25/100
Insufficient history management	§IV-B3	LLM agent		<b>√</b>					29%	29/100
Without final output	§IV-D1	Software components				<b>√</b>			88%	21/24
Improper error handling	§IV-D2	Software components	<b>√</b>						10%	10/100
Lacking System Management										
Improper LLM agent management	§IV-B8	LLM agent	<b>√</b>		<b>√</b>				14%	13/92
Privacy violation	§IV-D4	Software components						<b>√</b>	58%	11/19
Inefficient memory management	§IV-E2	system	<b>√</b>		<b>√</b>				9%	9/100
Resource contention	§IV-E1	system	<b>√</b>		<b>√</b>				15%	2/13
Mismatched speed between LLM and downstream tasks	§IV-E3	system	✓		✓				15%	2/13
Total number of benchmark applications with multiple type of defects								98%	98/100	

<sup>\*</sup> In the *Impact* column, from left to right, ST refer to fail-stops, IC refer to incorrectness, SL refer to slower execution, UI refer to unfriendly user interface, TK refer to more tokens, and IS refer to insecure.

between multiple components, while that specific component is believed to be responsible for eliminating such failure.

# B. Defects Located in LLM Agent

While LLMs have outstanding performance on various tasks, an incorrect integration would degrade the overall correctness and efficiency of software systems or even lead to fail-stop failures. In our benchmark suite, *all* applications suffer problems when integrating LLM agents.

1) Unclear context in prompt: Large language models (LLMs) suffer hallucination problems, especially when their prompts do not include enough information [24]. Due to the nature of generative models, LLMs are likely to produce grammatically coherent, contextually relevant, but semantically incorrect text outputs, e.g., non-existent quotes, false historical events, or even spurious scientific facts. In LLM-enabled applications, the unreliability of LLM agents could easily transmit to the tightly-integrated software components and even downstream tasks [14], [25]. Therefore, the LLM agent should construct clear and informative prompts to alleviate hallucinations. However, around a quarter of the benchmark applications failed.

Take **ChatIQ** [26], a chatbot for Slack platform, as an example. It is expected to answer questions according to the chat history and uploaded text files. Unfortunately, it is very likely to provide fictive responses when asked about the specialty foods of certain cities, *i.e.*, claiming that an inland city produces seafood. In another case, when the user asks about the meeting after uploading an invitation mail of work

plan discussion, it responds with topics that are not mentioned in the mail: "In addition to the work plan, we will also discuss arrangements for our annual gathering and a new employee training plan."

Developers may easily blame the inner flaw of LLM itself. While LLM hallucination is an unresolved problem, the software's incorrect behavior is not just caused by LLM itself. Actually, such hallucination could be alleviated through improving the prompt design [27]. The former failure could be resolved by enabling the RAG framework or online search module to provide external knowledge. For the latter, it would generate less incorrect responses by including clear instructions in the prompt template, *i.e.*, "Please precisely answer according to the given file."

2) Lacking restrictions in prompt: The LLM agents control LLM behavior through prompts. Besides guiding LLM to complete certain tasks, the prompts also include instructions that restrict LLM not acting in a certain way. Similar to conventional software, developers tend to spend most efforts to ensure the core functionality (enabling LLM to perform the intended actions), but ignore to handle corner cases (preventing LLM from performing unexpected actions). Due to the infinite input space of LLMs, it is hard for developers to design test cases that have high semantic coverage. Therefore, developers are unlikely to discover all unexpected behaviors and add restrictions in the prompt. Around 19% applications in our benchmark suffer such a problem.

RealChar [21] is an application designed to simulate

certain characters and chat with users (Figure 2). While expected to keep role-playing, it generates out-of-character responses from time to time. For example, when asked "Are you an AI?", it will admit that it is an LLM without hesitation. Similarly, when invoking OpenAI GPT-3 model without proper restrictions, it will answer the question of "How can I hack into someone's social media account?" frankly, leading to serious ethical and legal problems.

The most critical step in tackling this problem is to explore the output space of LLM agents and identify the unexpected responses, which require thorough in-lab testing (alpha testing) and also large-scale user testing (beta testing). Once identified, one may avoid them with a combination of fine-grained prompt instructions and output validation to restrict LLM agents' behavior.

3) Insufficient history management: For applications that involve multi-turn human-machine interactions (i.e. chat robots, text editors), in order to generate responses within the dialogue context, the LLM agent manages the recent history, including inputs and responses. When lost track of the history conversation, it is likely to (a) provide contextually incorrect answers when the user refers to the history; or (b) perform operations that conflict with earlier ones. In our benchmark suite, 27% applications have such problems, degrading the software correctness. Note that, the long-term history and RAG data are typically managed by the vector database, which will be discussed in Section IV-C.

As LLM's transformer structure naturally remembers recent activities, it is more likely to forget when the history accumulates. For example, **PDF-chatbot** [28] incorporates GPT-4 to comprehend PDF documents and answer user questions. Its conversation module is expected, but unfortunately fails, to retain chat history across interactions. As a consequence, after the user informs the author of a PDF document, it correctly answers the question of "Who is the author?". However, after 4 to 5 rounds of conversation, it replies "I do not have access to such information" instead, indicating its forgetting. As another example, the task management application babyAGI [29] suggests a list of tasks of a certain topic given by the user. However, it simply displays the response of LLM, without examining these generated tasks. Therefore, its suggestions are increasingly repetitive when the user continues asking for more tasks. Similarly, the repetitive response of Godmode-GPT [30] leads to repeated execution on failed task commands, wasting computation resources.

Such a forgetting problem greatly harms the functionality and usability of the user interface of multi-turn conversation. Although end-users could resolve the forgetting problem by repeating their earlier inputs, it actually defeats the purpose of using the application — reducing human efforts. One potential solution is maintaining a short summary of key information of past conversations, and always appending it when constructing prompts. Another other solution is validate LLM responses using execution history.

Fig. 3. Expected LLM agent output format in h2oGPT [33]

4) Missing LLM input format validation: Integrated in software, LLM agents take the textual output of the upstream tasks to construct its prompt. While LLMs' interface accepts all text strings within a certain length, they are only capable of handling a subset of text format (i.e. markdown syntax, JSON, CSV, etc). If the software fails to validate the input format, the LLM agent is likely to provide incorrect responses or even lead to software crashes. Among all the applications in our benchmark suite, 24% lack input format validation.

For example, **IncarnaMind** [31] supports comprehending text and PDF documents. While the interface allows users to upload Markdown files as text documents, the LLM agent actually fails to recognize the Markdown syntax from time to time. A potential fix is removing these syntax and converting them to plain text through rule-based approaches. Even for the supported PDF documents, if the software does not recognize text inside it, an "list index out of range" exception will be thrown out. As another example, **AppifyAi** [32], a code generator, allows users to upload CSV and Excel files, but lacks a module that converts them to the format that LLM could recognize.

Many developers are unaware of LLM's requirement of clear and standardized text, as its specification mainly focuses on the length of input text and suffixes of uploaded documents. Therefore, almost all context-based QA applications in our benchmark suite do not examine surface-level pattern of the input text. To tackle this problem, we strongly recommend developers carefully design input validation algorithms and maintain a whitelist of handleable file formats.

5) Incompatible LLM output format: Besides input validation, integrating LLMs into the software systems also requires converting their output to be compatible to the downstream tasks. LLMs support a wide spectrum of output formats, including structured/semi-structured text and code. However, their downstream tasks typically only support a subset of them. Sometimes, the downstream tasks perform rule-based string operations and have explicit format requirements: following certain syntax, the existence of certain keywords, etc. Sometimes, the responses have implicit requirements when displayed: the ordering of content, text style, etc. If the LLM agent fails to provide compatible output, it would lead to bad user experience, software misbehaviors, or even fail-stop failures. In our benchmark suite, around 13% of applications suffer such problems.

While the semantic content of LLM responses is usually reliable, it is quite hard to restrict a generative model to output in a strict format. An example is **h2oGPT** [33], a document

processing application that supports various file formats. When extracting text snippets from a longer article, the LLM agent does not retain the original line breaks and other text formats, which harms the readability. As another example, **babyAGI** is expected to remain the list order after updated, but often wrongly re-order them.

Some applications also apply rule-based processing (*i.e.* decoding, string operations), where the incompatible output is likely to cause software crashes. The finance module of **h2oGPT** requires a JSON-format string from the LLM agent, as shown in Figure 3. However, the LLM agent constructs tuple-format strings from time to time, leading to unexpected decoding failures. Even when the LLM output passes JSON decoding, the software will misbehave if it misses a certain key or contains an incompatible value (*i.e.*, a timestamp of wrong format).

There is no silver bullet for the LLM agent to tackle this problem, due to the different requirements from various downstream tasks. Instead, developers should design task-specific solutions to re-order and re-structure the LLM output format. The developers of **h2oGPT** could match the text before and after processing, and align them with rule-based approaches, and the developers of **babyAGI** could keep track of each list element.

6) Unnecessary LLM output: LLMs tend to provide long responses when not restricted by instructions or computation resources. Therefore, the LLM agent is likely to output unnecessary content. Some developers may accept it as all the required information is provided. However, considering the additional effort of retrieving useful information, these unnecessary outputs greatly harm the service quality of the entire application. There are two major sources of unnecessary outputs: (1) the LLM over-generalizes a question and provides extra information that is not required; (2) the LLM repeats or rephrases its earlier responses and provides redundant information. Among all the applications in our benchmark suite, 24.0% suffer such problems.

privateGPT [34] utilizes Vicuna-7B [35] to generate document ingestion and answer user questions. Sometimes, it would appends meaningless text after a short answer, i.e. "I don't know.]]>### Jack ### Sally ### Charlie ### David". As another example, LLMChat [36] incorporates GPT-3.5 to realize the similar feature. It is expected to answer "J.K. Rowling" when asked "Who is the author of the Harry Potter series?". However, besides the author name, it also outputs a long paragraph introducing the main characters, plots, writing styles, and other unrelated information. Code-Review-GPT [37] also tends to generate overly polite and verbose code reviews, while users typically only care about bug reports.

To alleviate unnecessary outputs, the LLM prompts should clearly specify the required information and instruct the LLM to respond briefly. Another solution is to explicitly set the number of generated tokens, either through prompt instructions or API parameters (*i.e.* –n flag of OpenAI APIs).

7) Exceeding LLM context limit: Facing constrained memory and limited computation resources, most cloud service providers set a maximum token length for their LLM services [1], [38]. Even for local LLMs running on a powerful machine, extra-long inputs would lead to accuracy issues, due to the limitations of the attention mechanism adopted by LLM architectures. In practice, the LLM agent limits the context length, which counts all the tokens inside the input and the corresponding output. If one LLM invocation exceeds the context length limits, the LLM agent will truncate the output and provide an incomplete response. This problem is particularly severe when (1) the vector database is involved in prompt construction, or (2) the software maintains a long dialogue history. Among our benchmark suite, 32% of the applications contain such defects.

In many applications, the token quota is likely exhausted by detailed instructions, long text to analyze, and uncompressed history. Every time invokes LLM, **Quivr** [39] sends the entire chat history to the LLM to ensure an in-context response, and thus quickly reaches the token limit. Similarly, **ChatDocs** [40] constructs the prompt with all text extracted from PDF documents, which easily exceeds the token limits and triggers CUDA out-of-memory error. Clearly, developers could 1) compress instructions through prompt engineering, 2) limit user input length through UI design and data chunking; and 3) abridge history through NLP (natural language processing) and RAG techniques. Note that, even executed on a powerful server, the application could easily exhaust the enlarged token quota if the LLM agent does not carefully construct the prompt.

8) Improper LLM agent management: In current software framework, the applications have to initialize an agent instance before invoking the LLM. Sometimes, an application would initialize multiple agents for different tasks or users. These agents records and maintains the configurations, execution history, and prompt constructions of LLMs. If LLM agents are not properly managed, the application will face problems of data loss, broken data pipeline, and performance degradation. This defect eixsts in 14% of the applications that manages multiple LLM agents.

Even using LangChain and other frameworks that warp LLMs and provide unify APIs, developers still need to systematically manage the LLM agents. Take **DB-GPT** [41], a multisource knowledge management application, as an example. While expected, it does not solidify the LLM agent to store its configurations and history persistently. Therefore, all data will be flashed out when software terminates, greatly harming user experience. As another example, **LlamaChat** [2] fails to initialize LLM agent with Vicuna-7b and other models, failing to provide real-time conversation with users. Given these observations, developers should carefully design data storage and error handling mechanism, preventing data losses and unexpected fail-stops. When an LLM agent instance fails, The application should be able to restart it or switch to another agent without data loss.

#### C. Defects Located in Vector Database

In LLM-enabled applications, vector databases provide important support for intelligence features, serving as the long-term memory of language models. The incorrect usage of vector databases is likely to result in software misbehaviors, harming service quality and user experience. Around 35% of our benchmark applications does not correctly use the vector database. While developers are likely to criticize the RAG algorithm and neglect the coordination with software [42], there is a chance to eliminate the incorrect behavior through a better integration of vector databases.

1) Knowledge misalignment: Vector databases store and manage knowledge entries. To create these entries, the application first extracts text from documents of various formats, and splits text into several chunks, each containing a piece of cohesive knowledge unit. Each chunk is then tokenized and embedded into a semantic vector, which forms a knowledge entry together with the original text chunk. If the data chunking and tokenization are not performed in an accurate and robust way, the LLM-enabled software application would misbehave due to the low-quality knowledge base, or suffer memory overflow due to inefficient memory management. In our benchmark suite, around 28% of applications have knowledge misalignment problems.

Sometimes, an application fails to extract data chunks from files of various sizes. For example, **AutoGPT** [43] encounters failure when processing both large and small files. It triggers out-of-memory error when tokenizing data chunks from large JSON files, due to the large chunk size. Meanwhile, it also ignores small files (*i.e.* less than 150 characters), wrongly regarding them do not contain any data.

In other cases, an application fails to extract intact knowledge units due to bad chunking positions. **FastGPT** [44] simply splits data chunks according to character counts. Therefore, when given structured data (*i.e.* tables), it is likely to break data integrity and fail to obtain cohesive knowledge units. If the chunking position is moved to the end of a table or sentence, the knowledge entries will become much more feasible.

Occasionally, an application creates in-cohesive knowledge unit, as the source file contains much irrelevant information. **h2ogpt** [33] is an example. It tends to create large knowledge units, which confuses the LLM agent when retrieved. To tackle this problem, developers could utilize keyword extraction, TF-IDF, clustering, and other light-weighted approaches to measure the cohesiveness of knowledge units, and apply finer granularity data chunking when needed.

2) Conflict knowledge entries: In the vector databases, the semantic vectors serves as both identifiers and indices of an knowledge entry. Similar as relational databases, developers have to carefully design these identifiers to ensure software correctness and reliability. Particularly, embedding different text data into same feature vector would lead to severe correctness problem: the earlier data would be overwritten and suffer data loss! In our benchmark suite, we observe that 20% applications contain such defect.

```
idef embedTextInput(textInput):
   const result = await this.embedChunks(
   textInput);
4+ Array.isArray(textInput)?textInput:[textInput]);
```

Fig. 4. A fix of improper text embedding in anything-llm [46].

Take **Webui** [23] as an example. When updating its knowledge base with a new document, due to a semantic vector collision, it overwrites the knowledge entry obtained from a previous document with similar topics. Similarly, **Godmode-GPT** [30] wrongly overwrites a knowledge entry when expected to append new content to it. Clearly, developers should carefully design the embedding mechanism and manage the potential conflict knowledge entries, instead of simply relying on the existing vector database design.

3) Improper text embedding: The knowledge entries are indexed by their semantic vectors when stored in vector databases. Their correct retrieval highly relies on the correct embedding — the entries containing similar knowledge topics should also have similar semantic vectors, and vice versa. An inaccurate embedding would cause RAG techniques to decrease LLM accuracy and efficiency, and thus harm service quality of the entire software. In general, the developers have to carefully deal with text characteristics in three different levels: 1) encoding format, i.e. encodings and natural languages; 2) surface-level pattern, i.e. writing styles and structures; and 3) deep-level pattern, i.e. semantics and topics. In our benchmark suite, around 34% applications improperly manage text embedding.

QnA [45] is an in-context QA application. While its LLM agent supports a wide range of natural languages, it uses ISO-8859-1 encoding when embedding the text, which only supports languages from Western Europe. Therefore, the software will respond garbled text when the user upload documents in Asian languages. As another example, Anything-LLM [46] improperly interprets text structures and truncates words in the middle, which the embedding model could not understand. However, the software correctness could be greatly improved by a simple format conversion. Figure 4 shows an accepted fix of function embedTextInput in Anything-LLM.

4) Improper similarity search: When accessing a vector database, the similarity search algorithm identifies the most pertinent data that matches the query. It plays a critical role in constructing context for the LLM agent such that serves the software downstream tasks. If the similarity search fails, the LLM agent will provide inaccurate or out-of-context responses, resulting in software misbehaviors. We observe such defects in 19% applications that conduct similarity searches in their core function modules.

Generally, the query to the vector database should concentrate on the topic of targeted knowledge, otherwise, the relevant entries are unlikely to be retrieved. For example, the task management application **babyAGI** queries the vector

database with a general task (*i.e.* prepare a farewell) from the user, but fails to retrieve relevant data with such a vague description. In fact, **babyAGI** also generates several concrete steps (*i.e.* invite guests, order food, and decorate house) for the user to accomplish this general task. If query with these concrete sub-tasks individually, the vector database is able to find the knowledge entries that have similar semantic vectors to the query.

Besides failing to retrieve relevant data entries, retrieving irrelevant ones also harms software correctness. Sometimes, the vector database provides more information than required: it returns the correct knowledge entry together with others that have close feature vectors. If the application does not validate the output of vector databases, these irrelevant data entries would end up constructing misleading context for the LLM agents. For example, when **ChatDocs** [40] queries vector databases for documents of a certain topic (*i.e.* climate change), it obtains a list of unrelated references (*i.e.* cooking recipes), due to mentioning a same entity (*i.e.* temperature). This failure could be alleviated by a relevance validation before appending them to the LLM prompt, either through similarity scores from the vector database or utilizing a small NLP model.

# D. Defects Located in Software Components

In an intelligence software system, the AI-related components (*i.e.* LLMs and vector databases) typically play central characters. Meanwhile, the software components around them also provide important support to ensure the functionality and performance of entire software systems, including data/control flow logic, UI components, and coordination across different modules. Without the reliable integration of software components, the software is likely to misbehave. For instance, a defect in a UI component could result in an unresponsive button, while a defect in data flow is likely to cause data loss or even corruption.

In this section, we focus on the defects that emerge from general software modules that interact with LLMs and vector databases.

1) Without final output: The LLM agents support multiturn interaction, allowing users to instruct it in a step-bystep or feedback-based way. This is typically visible in incontext QA and chat robot applications. However, the users of LLM-enabled software applications usually expect an "onexit" conclusion of the entire conversation, which serves as the final output. Otherwise, although finishes all the tasks, the latest output of the LLM agent would remain intermediate or incomplete answer, making a normal software termination seem like an unexpected crash. We observe this problem in 22 of 24 applications that have multi-turn conversations.

Take **LocalAGI** [47] as an example. After accomplishing an article according to user requirements, it allows the user to request revision in a conversation-like manner. During the revision process, it regenerates a certain part of the original article according to user requirements. However, it simply

stops without outputting the final version of the entire article when the user finishes the revision process. Making things worse, due to its infinite loop design, **LocalAGI**, from time to time, gets stuck in the revision step and endlessly regenerates its response until the entire software is manually terminated. This further prevents the application from providing a final output.

Actually, missing final output is a common problem for conversation-based applications, as applications have no idea whether the user has finished his/her tasks until explicitly noticed. To tackle this problem, we recommend developers design an "on-exit" behavior to provide a final output that summarizes all the intermediate results in the history conversation.

2) Improper error handling: Error handling is a classic problem of software engineering. The integration of LLM agents and vector databases further challenges this task. These two components are data-centered and have loose interface format requirements. However, the conventional software components are logic-centered and have strict interface specifications. Therefore, LLM-enabled applications are more likely to trigger errors and exceptions during execution. While most the benchmark applications have implemented exception handlers, not all of these handlers are feasible. In fact, we have triggered fail-stop failures in around 10% of application.

**DB-GPT** [41] is a central platform that translates users' natural language requests to SQL queries and fetches data from SQL databases. It will receive an error code from the SQL server if the LLM-generated SQL query contains syntax error and fails parsing. While expected to automatically fix the syntax error, or at least to guide the user to resolve it, **DB-GPT** simply output "Application error: a client-side exception has occurred." without any detailed information or fixing attempts. We have conducted an experiment on the all the 1,534 natural language requests from BIRD development dataset [48], and received syntax error reports for 24% of the generated SQL query. Developers may easily blame the inability of LLM or insufficient schema information from RAG. However, 70% of these syntax errors could be fixed by rule-based solutions or re-generation by additionally proving the error message to the LLM agent.

Worse still, some applications do not even realize the existence of these errors. Langchain-Chatchat [49] wrongly requests an internet connection when accessing a local LLM. It crashes with Internal Server Error and Connection Refused Error when unconnected to the internet, which is unlikely to be exposed during testing. Therefore, it lacks an exception handler for these errors.

3) Low-Frequency interactivity: When the LLM agent or vector database is deployed on a remote server (including cloud services), the server typically sets a timeout limit for the connection from clients. If the client sends requests at a low frequency, it is likely to lose connection with the server and suspend operations, leading the application to shut down unexpectedly. Moreover, since LLM agents are

stateful and require query history, the re-connection would also harm the core intelligence functionality of the application and user experiences. We observe such low-frequency interactivity problems in around 90% applications.

**AutoGPT** [43] supports a conversation-based user interface and allows users to enter requests at any time. It incorporates urllib3 library [50] to open a session and access LLMs on the Open AI cloud server. However, due to the time-out mechanism, if the user requests at a low frequency, the application will lose connection with the cloud server and crash. To tackle this problem, the developer could either change the timeout settings of the timeout settings, or send a 'heartbeat" request periodically to maintain the connection.

4) Privacy Violation: Expanding the scope from RAG-enhanced LLM algorithms to the entire software system, the privacy issue arises. Here, we focus on the privacy violation that is unique to LLM-enabled applications. In traditional software, users access data through the operating system (OS) which validates user identity and grants access. In LLM-enable applications, the LLM agent acts as a super-user and requests data to OS on behalf of the end-users. Meanwhile, the LLM agent itself lacks an identity authentication mechanism. If the application does not properly isolate the data of different users, the LLM agent will access unauthorized data when it makes incorrect inferences or encounters malicious requests. In our benchmark suite, 11 of 19 applications that invoke system calls violate user privacy.

As a multi-user platform, AutoGPT [43] is expected to manage file ownership and prevent unauthorized access from users. However, it allows the LLM agent to read and write all files within its workspace, without examining the user identity. One could easily read or damage the file belonging to others, through injection attacks [51] on the LLM agent. While convenient, developers actually should not grant all system privileges to the LLM agent, as system root access should not be granted to an untrustworthy object. Instead, they should keep track of the original user request of each LLM agent behavior, and grant system privileges according to the user identity.

# E. Defects Located in System

The system environment allocates resources to the LLM-enabled applications and carries out their execution. Both the LLM algorithm and vector database require much computation and memory resources to support their functionality, which places extra demands on system management. When the application fails to properly manage systems resources, it is likely to suffer concurrency problems, out-of-memory, resource contention, and other system defects.

1) Resource contention: Besides memory, the LLM agents and vector databases also require much computation resources. When deployed on hardware with limited resources, especially for end-user computing scenarios, the LLM-based applications are likely to face resource contentions when the workload is high. Such resource contention would lead to

```
model = load_model('ChatGLM-6B-int4')
inference_with_int4_model()

+ del model  # release CPU memory

+ torch.cuda.empty_cache()  # release GPU memory

model = load_model('ChatGLM-6B-int8')
```

Fig. 5. A fix of inefficient memory management in ChatGLM-Web [23].

slower execution or even hangs. Clearly, the developers should limit system resource requests from their application, and design solutions to recover from resource contention, including downgrade services and limit user numbers.

This problem affects 2 of 11 applications that execute LLM or vector database locally. For example, **PrivateGPT** [34] allows users to configure the number of maximum parallel threads (n\_threads), allowing embedding multiple data in parallel. However, if the LLM agents and vector databases already occupy many CPU cores, a large n\_threads would lead to resource contention and slower software execution. As another example, **DB-GPT** hangs when responding to users in multiple LLM agent instances at the same time. We trigger this problem by simultaneously launching 2 LLM agents with chatglm3-6b model, on a Linux server with one 24GB RTX 4090 GPU.

2) Inefficient memory management: Both LLM agents and vector databases have high memory consumption, necessitating efficient memory management. Memory consumption further arises when the application handles large volumes of data or executes complex queries. Inefficient memory management would lead to performance degradation or even out-of-memory crashes. Around 9% of our benchmark applications contain this defect.

**ChatGLM-Web** [23] is an example. It supports several local LLMs, and each of which could be successfully loaded to the GPU memory. However, if it switches to another model within the same execution, an out-of-memory error occurs — the old model, although no longer useful, remains in the GPU memory. It turns out that an explicit command is required to release the memory resources, as shown in Figure 5.

Even for applications that invoke LLM cloud services, the execution of vector databases and communications between software components still require much memory to process, transfer, and store feature vectors.

3) Mismatched speed between LLM and downstream tasks: In some LLM-enabled applications, the LLM agents process streaming data and continuously send data to the corresponding downstream tasks, fully utilizing their sequence-to-sequence feature. The speed mismatch between LLM agents and downstream tasks would lead to various performance problems: faster LLM agents could lead to large-scale pending data, and faster downstream tasks could lead to severe I/O block or even fail-stop failures. We discover this defect in 2 of 13 applications that have time-sensitive downstream tasks.

When initializing the vector database from a list of files, langchain-chatbot [52] fetches a new batch of LLM responses

right after it finishes processing the earlier one, assuming that the LLM agent is faster than its downstream tasks. However, when experiencing a network delay or switching to a more resource-consuming LLM model, it is likely to attempt to fetch data from an empty queue and trigger software crashes. As another example, **FastGPT** utilize an HTTP module to manage the data transformation and implement the user interface. Unfortunately, this HTTP module does not support streaming inputs and blocks until the LLM agent finishes generation, which harms software performance.

#### V. THREAT TO VALIDITY

**Internal threats to validity.** The test inputs used in our profiling may not represent the actual workload of end-users. The issues collected and confirmed in our study may not represent all the software defects.

**External threats to validity.** We only study LLMs designed for general language and code tasks, excluding multimodal LLMs and fined-tuned LLMs for specific tasks. Our study only covers a subset of vector databases and frameworks. We only study open-source projects on GitHub, with no access to those closed-source commercial projects. The 103 applications in our benchmark suite may not represent all real-world applications.

# VI. RELATED WORK

#### A. LLM and RAG

LLMs have revolutionized various AI research fields and enabled advanced applications [53], [54], including human-like conversations [55], [56], mathematical reasoning [57], planning [58], control [59], and software engineering [60]–[65]. Recently, fine-tuning [17], prompt engineering [18] and ensemble [66], [67] have been proposed to improve LLM capability on specific tasks. However, LLMs still face trust-worthiness and efficiency problems [11], [24], [68]. Retrieval-augmented generation techniques [7], [8] are then proposed to utilize external knowledge to enhance LLMs in question-answering [69], planning [70], coding [71]–[74], and other tasks. These works focus on LLM and RAG algorithm designs, instead of how to integrate them into software applications.

One recent work [75] has explored remote code execution (RCE) vulnerabilities of LLM frameworks. It only studies the security problems. Instead, our work studies a wider scope of engineering challenges and integration failures in real-world applications that use RAG-enhanced LLMs.

# B. AI-enabled software

Prior works have studied developing and maintaining AIenabled software throughout the entire life cycle.

One line of works study the quality of neural networks, through testing [76]–[79], monitoring [80]–[82] and repairing [83]–[86]. Some works study deep learning frameworks [87]–[90] or compilers [91], [92]. These works focus on constructing AI models, instead of using them.

Another line of works explore AI usage in real-world applications. Much research has been done for the development challenges [93], [94] and deployment problems [95], [96] of AI-enabled software, including mobile applications [97], [98], cluster infrastructures [99], and general systems [100] Other works studies the software integration of cloud AI services [10], [14]–[16] All of these studies focus on traditional AI designed for specific tasks, which typically have categorical or structural outputs. They do not address the unique challenges of general-purpose LLMs.

#### VII. CONCLUSION

RAG-enhanced LLMs have been widely integrated into real-world applications to perform various intelligence tasks. This paper conducts a comprehensive study to understand the challenges of integrating these RAG-enhanced LLMs into software systems. We have investigated 100 open-source LLM-enable software and manually studied 3,000 issue reports, finding that integration defects are widespread in real-world applications. We summarize 19 defect patterns that cause functionality, efficiency, and security problems. We hope that this work could aid LLM-enabled software development and motivate future research.

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