

CAM: A Causality-based Analysis Framework for Multi-Agent Code Generation Systems

ZONGYI LYU, The Hong Kong University of Science and Technology, China

ZHENLAN JI*, The Hong Kong University of Science and Technology, China

SONGQIANG CHEN, The Hong Kong University of Science and Technology, China

LIWEN WANG, The Hong Kong University of Science and Technology, China

YUHENG HUANG, The University of Tokyo, Japan

SHUAI WANG†, The Hong Kong University of Science and Technology, China

SHING-CHI CHEUNG, The Hong Kong University of Science and Technology, China

Despite the remarkable success that Multi-Agent Code Generation Systems (MACGS) have achieved, the inherent complexity of multi-agent architectures produces substantial volumes of intermediate outputs. To date, the individual importance of these intermediate outputs to the system correctness remains opaque, which impedes targeted optimization of MACGS designs. To address this challenge, we propose CAM, the first Causality-based Analysis framework for MACGS that systematically quantifies the contribution of different intermediate features for system correctness. By comprehensively categorizing intermediate outputs and systematically simulating realistic errors on intermediate features, we identify the important features for system correctness and aggregate their importance rankings, facilitating comprehensive analysis of MACGS.

We instantiate CAM on representative MACGS across multiple backend LLMs and datasets and conduct extensive empirical analysis on the identified importance rankings. Our analysis reveals intriguing findings: first, we uncover context-dependent features—features whose importance emerges mainly through interactions with other features, revealing that quality assurance for MACGS should move beyond module-level validation to incorporate cross-feature consistency checks; second, we reveal that hybrid backend MACGS with different backend LLMs assigned according to their relative strength achieves up to 7.2% Pass@1 improvement, underscoring hybrid architectures as a promising direction for future MACGS design. We further demonstrate CAM’s practical utility through two applications: (1) failure repair which achieves a 73.3% success rate by optimizing top-3 importance-ranked features and (2) feature pruning that reduces up to 66.8% intermediate token consumption while maintaining generation performance by pruning low-importance features. Our work provides actionable insights for MACGS design and deployment, establishing causality analysis as a powerful approach for understanding and improving MACGS.

CCS Concepts: • Software and its engineering → Software testing; Causal analysis.

Additional Key Words and Phrases: multi-agent systems for code generation, causal analysis

1 Introduction

Multi-Agent Code Generation Systems (MACGS) have emerged as a transformative paradigm in automated software development, demonstrating remarkable capabilities in generating high-quality code through sophisticated agent collaboration [11, 22, 24, 45, 68]. By decomposing complex programming tasks into specialized subtasks and coordinating multiple agents with distinct roles, MACGS have achieved substantial improvements over single-LLM approaches [17, 18, 41, 63] across diverse benchmarks [2, 6, 33, 67]. Despite their demonstrated effectiveness, MACGS present fundamental challenges in understanding and analyzing their intermediate outputs. The multi-agent architecture inherently produces diverse and complex intermediate outputs across agents [60], making it exceptionally difficult to comprehend their impact on the overall system. This opacity substantially compromises the robustness of these new-generation software—LLM agent-based systems—and impedes further optimization of MACGS designs.

*Corresponding authors.

†Corresponding authors.

Several approaches can be applied to analyze intermediate outputs in MACGS, yet each suffers from notable limitations. Manual analysis, while intuitive, is prohibitively expensive and inherently subjective, limiting its scalability and reproducibility. LLM-based evaluation methods [42, 70, 73] offer automation but exhibit low accuracy and introduce reliability concerns, as shown by our preliminary study in Sec. 3.2. Currently, MACGS developers predominantly rely on all-but-one ablation designs that disable entire agents or modules to assess their impact on final code quality [11, 35, 68]. However, such coarse-grained approaches fail to capture the nuanced influence of specific intermediate components and lack generalizability across different MACGS architectures. Collectively, these limitations underscore the need for a fine-grained analysis method that balances analytical rigor with practical cost.

To address these limitations, we leverage *actual causality* [20] to analyze the causal relationships between intermediate outputs and final code correctness in MACGS. However, conducting causal analysis on MACGS requires overcoming substantial technical challenges. First, it is challenging to decompose complex intermediate outputs into structured features and construct the causal graph for causal analysis. Second, causality-based methods typically rely on a substantial amount of data to guarantee the reliability of analysis [12, 39, 64]. In the context of MACGS, this requirement manifests as the systematic simulation of a variety of realistic execution states, particularly errors, which is a non-trivial task [60]. Third, the computational cost of MACGS execution is another noticeable obstacle. Unlike traditional software systems [53, 59] that operate with minor cost, merely one single execution of MACGS may involve multiple LLM calls, with up to 10^4 LLM token consumption [60]. This prohibitive cost makes it infeasible to exhaustively explore all execution states of the object software like prior work [12]. Instead, it is imperative to design an efficient execution state exploration algorithm that can strategically make trade-offs between analysis comprehensiveness and computational cost.

To tackle these challenges, we present CAM, the first **Causality-based Analysis** framework for MACGS to identify the relative importance of different intermediate components to final code correctness. Specifically, we first develop a systematic categorization method to model complex intermediate outputs into a variety of variables, or *features*, which capture key aspects of intermediate outputs from various perspectives and are generalizable across various MACGS. We then construct a causal graph based on these features to facilitate subsequent causal analysis. To systematically simulate realistic errors, we design an LLM-based approach that comprehensively conducts counterfactual intervention on intermediate outputs. Additionally, regarding the execution state exploration challenge, we introduce a novel notion, *influence set*, that reflects the unique error propagation mechanism of multi-agent systems considering LLMs' self-correction ability [10]. Based on this insight, our proposed algorithm can efficiently prune unnecessary states and achieve an ideal balance between reliability and computational cost.

To gauge the reliability of CAM, we empirically validate CAM's reliability by comparing its identified feature importance against manual analysis, demonstrating strong agreement with Kendall's correlation coefficients [29] ranging from 0.76 to 0.91. On this basis, we conduct a comprehensive analysis of feature importance patterns that lead to intriguing findings for MACGS design and deployment. First, we uncover a previously overlooked phenomenon: *context-dependent features*—features whose importance manifests primarily through interactions with other features. For instance, in 78.8% of cases, `Program_Lang` (programming language for code implementation) affects the system correctness only when simultaneously intervened with other features. This context-dependency indicates that failures arise not only from individual feature errors, but may also stem from subtle incompatibilities between seemingly correct intermediate features. This finding reveals a critical insight for improving MACGS: quality assurance for MACGS should move beyond module-level validation to incorporate cross-feature consistency checks. Furthermore, we

reveal that different backend LLMs exhibit distinct capabilities across subtasks, motivating hybrid multi-backend architectures for MACGS, where different backend LLMs are assigned to specific stages. Empirical validation of a hybrid backend MACGS achieves up to 7.2% Pass@1 improvement compared to uniform backend configurations, underscoring the potential of hybrid architectures as a promising direction for future MACGS design. Moreover, we demonstrate CAM’s practical utility through two causality-guided downstream applications: (1) failure repair, which achieves a 73.3% success rate by optimizing only the top-3 ranked features, and (2) feature pruning, which reduces intermediate output token consumption by up to 66.8% while maintaining or even improving code generation performance.

Overall, we summarize our contributions as follows:

- We identify and address a critical challenge in MACGS: understanding how intermediate outputs causally influence final code correctness. For the first time, we introduce actual causality to systematically analyze MACGS, establishing causality analysis as an effective approach for understanding and improving MACGS.
- We propose CAM, a comprehensive causality-based analysis framework that automatically quantifies each intermediate feature’s importance on system correctness. CAM first models complex intermediate outputs into structured features, and then systematically identifies critical features by efficiently conducting counterfactual interventions through influence set analysis.
- We conduct extensive empirical analysis on representative MACGS across multiple backend LLMs and datasets, yielding actionable insights for MACGS design and deployment. We further demonstrate the practical utility of CAM through two successful applications: causality-guided failure repair and feature pruning.

2 Background

2.1 Multi-agent Code Generation Systems

With the rapid advancement of LLM-based agents [21, 66, 69, 71], multi-agent code generation systems (MACGS) have emerged as a predominant paradigm for automated code generation [11, 22, 24, 45, 68]. The fundamental methodology underlying MACGS involves decomposing the code generation process into a sequence of specialized subtasks, each delegated to distinct agents with specific responsibilities. The division of labor enables MACGS to develop a more comprehensive and nuanced understanding of programming tasks compared to single-LLM approaches [15, 19, 25].

A typical workflow of MACGS includes three main phases: planning, coding and refinement [21, 36, 68]. Upon receiving a user’s problem specification, MACGS conduct multi-step planning where the original problem undergoes systematic decomposition, requirement analysis, and implementation design. This planning process serves as a critical guidance mechanism for subsequent code generation [37], producing substantial intermediate outputs that capture different facets of problem understanding. Following the planning phase, MACGS proceeds to generate code based on the planning outputs and conducts iterative refinement to ensure code quality and correctness. Among the various MACGS architectures, MetaGPT [22] stands as one of the most influential and widely-adopted frameworks, inspiring numerous subsequent MACGS implementations [24, 38, 68].

While MACGS facilitate sophisticated problem solving, they generate substantial volumes of intermediate outputs except for the final code [60], including problem understanding, algorithm design, and implementation approaches [21, 36]. The individual contributions of these intermediate outputs to the final code remain opaque, which hinders the targeted optimization of MACGS [34, 51].

2.2 Actual Causality

As a canonical technique that is extensively applied to analyze complex software systems [3, 12, 39, 64], actual causality [20] is effective for identifying the underlying causes of observed behaviors and outcomes within intricate systems. Typically, actual causality proceeds by examining counterfactual scenarios on causal graph: given an observed outcome, actual causality determines which variables are the cause for the outcome to occur. In this paper, we leverage the following concepts in actual causality to systematically analyze MACGS.

Definition 1. (Causal graph). In actual causality, a causal graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ is a directed acyclic graph (DAG) that encodes the causal dependencies among variables in the system. Each vertex in \mathcal{V} represents a variable, and each directed edge $(V_i, V_j) \in \mathcal{E}$ indicates that V_i directly influences V_j . The acyclic structure ensures a well-defined causal ordering and prevents circular dependencies that would render causal analysis ill-posed. In this paper, we construct causal graph for MACGS through systematic decomposition in Sec. 4.1.

Definition 2. (Actual cause). An actual cause [20] is defined through three conditions (AC1, AC2, AC3) that respectively capture actuality, counterfactual dependence, and minimality. Formally, $\vec{X} = \vec{x}$ is an *actual cause* of ϕ in the causal setting (M, \vec{u}) if the following three conditions hold:

AC1 (Actuality): $M, \vec{u} \models \vec{X} = \vec{x} \wedge \phi$. This ensures that both the cause and the effect actually occur.

AC2 (Counterfactual Dependence): There exists a set \vec{W} of variables in \mathcal{V} and a setting \vec{x}' of the variables in \vec{X} such that if $(M, \vec{u}) \models \vec{W} = \vec{w}^*$, then: $(M, \vec{u}) \models [\vec{X} \leftarrow \vec{x}', \vec{W} \leftarrow \vec{w}^*] \neg\phi$. This condition captures the counterfactual dependence of ϕ on $\vec{X} = \vec{x}$ under the contingency $\vec{W} = \vec{w}^*$.

AC3 (Minimality): \vec{X} is minimal; no proper subset of \vec{X} satisfies AC1 and AC2: if $\{\vec{X}, \vec{Y}\}$ causes outcome ϕ but $\{\vec{X}\}$ alone suffices, then only $\{\vec{X}\}$ constitutes the actual cause, not $\{\vec{X}, \vec{Y}\}$.

In this work, we analyze the intermediate outputs of MACGS through systematically identifying the important outputs to system correctness, leveraging the definition of actual cause.

Definition 3. (Responsibility) The responsibility quantifies the relative importance of different causes. For a cause $\vec{X} = \vec{x}$ of ϕ , its responsibility is defined as:

$$dr(\vec{X} = \vec{x}, \phi) = \frac{1}{1 + |\vec{W}|} \quad (1)$$

where $|\vec{W}|$ denotes the minimum cardinality of contingency sets \vec{W} required to establish the counterfactual necessity of $\vec{X} = \vec{x}$. Intuitively, responsibility measures how many additional variables must be held or fixed for the causal effect to manifest. In this work, we measure the importance of different features in MACGS through aggregating their corresponding contribution, which is inspired by the concept of responsibility in actual causality.

3 Motivation

3.1 Significance of Intermediate Outputs

While MACGS demonstrate impressive capabilities in automated code generation, they suffer from notable robustness challenges [37]. The generation process in MACGS is inherently complex, involving multiple stages of information transformation across multiple agents [21, 36]. Consequently, errors introduced in the intermediate outputs can propagate through the pipeline and ultimately compromise system correctness [10]. To empirically investigate this impact, we randomly sample 100 failed cases from MetaGPT [22] and manually analyze their root causes. We identify three main failure causes: *Intermediate flaw* (flawed intermediate outputs

Table 1. Distribution and Recoverability of failure causes.

Failure Cause	Count	# Fixed
Intermediate flaw	83	78
Overthinking	12	4
Underthinking	5	2
Total	100	82

generated by agents), *Overthinking* (exceeding iteration limits without reaching solution), and *Underthinking* (premature termination before sufficient exploration). We then attempt to recover these failures and re-execute MetaGPT: for intermediate flaws, we manually correct the erroneous outputs; for overthinking and underthinking, we identify the problematic phase and prompted re-execution from that checkpoint, following existing works [58, 62]. As shown in Table 1, 83% of failures stem from intermediate flaws, substantially higher than overthinking (12%) and underthinking (5%), highlighting the importance of intermediate outputs in system correctness. Moreover, correcting intermediate flaws resolved 78 out of 83 cases, demonstrating that intermediate output errors are both the most prevalent and most recoverable. These findings underscore the criticality of systematically exploring the importance of intermediate outputs and analyzing their robustness and impact on the overall system.

3.2 Analytical Challenges and Limitations of Existing Methods

Despite their significance, the large volume of intermediate outputs generated by MACGS presents formidable analytical challenges. The complex dependencies among these outputs make it exceedingly difficult to disentangle their individual contributions to final outcomes, underscoring the pressing need for systematic analysis. Before introducing our proposed framework, we first examine existing methods and discuss their inherent limitations.

A straightforward approach to tackle this challenge is through manual inspection. Domain experts can examine failed code generation instances, trace through intermediate outputs, and determine the important parts. However, manual inspection suffers from severe scalability limitations and is inherently subjective, making it unsuitable for systematic evaluation.

An alternative approach leverages LLM reasoning capabilities [42, 70, 73]. We evaluate this through a preliminary study where we task state-of-the-art LLMs to identify important intermediate outputs responsible for MACGS failures and compare the results with human annotations. Specifically, we randomly select 100 MetaGPT failure cases and provide the LLM with all intermediate outputs and the final incorrect code. We then prompt it to identify failure-causing outputs. As shown in Table 2, even the best model (GPT-4o) achieves only 41% accuracy. This poor performance may stem from LLMs frequently identifying outputs merely correlated with failures rather than actually causing them, aligning with recent findings that LLMs struggle with analyzing complex chain processes [26, 30, 65].

Other approaches rely on all-but-one studies that remove entire agents or modules to examine their effects on MACGS performance [11, 38, 68]. However, such approaches suffer from significant limitations in analytical granularity. Agent outputs typically comprise multiple parts with distinct semantics and functions, yet all-but-one studies treat them as monolithic units [11, 24, 35]. This overlooks the intricate coupling among different parts: they are often cross-dependent within agents, and their collective effects on downstream performance are non-additive [7, 44]. Consequently, removing an entire agent conflates distinct contributions of different parts, yielding unreliable results that lack actionable insights. For example, in MetaGPT, the output of product manager can be decomposed into several semantic fields, directly disabling it fails to identify the individual contribution of each field. Therefore, we aim to answer the following critical question: how to systematically analyze and establish the intermediate outputs' importance on the output of MACGS?

Table 2. Accuracy of LLM-based automatic cause identification.

LLM	Accuracy
GPT-4o	41.0%
Qwen-2.5-Coder	37.0%
DeepSeek-Coder-V2	34.0%

3.3 Actual Causality for MACGS Analysis

As introduced in Sec. 2.2, actual causality [20, 43] provides an ideal foundation for analyzing MACGS intermediate outputs. Unlike correlation-based analysis [40, 46], which merely identifies statistical associations between intermediate outputs and failures, actual causality establishes genuine causal relationships through counterfactual reasoning and systematically conducts interventions to distinguish causation from correlation [12, 64].

As illustrated in Fig. 1, suppose MACGS receive the task of generating a stable sort function, with the following intermediate outputs: (1) Design D specifies a quicksort-based algorithm, and (2) Implementation steps I details the logic. The final code based on D and I implements quicksort, which is an unstable sort. Using correlation-based analysis, we might observe that both D and I are present in most failed executions of this task, but this does not tell us which was the actual cause. In contrast, actual causality systematically tests counterfactuals: Would replacing D with a bubble-sort algorithm fix the failure? Would replacing I alone suffice? Through these interventions, actual causality determines that D 's choice of quicksort is the minimal sufficient cause, as changing it resolves the failure regardless of I , while changing I alone cannot guarantee correctness.

Leveraging actual causality, we aim to develop a comprehensive framework specifically tailored for analyzing MACGS. However, conducting causal analysis on MACGS presents several challenges:

(I) Challenge of Causal Modeling. It is difficult to systematically decompose complex intermediate outputs of MACGS into meaningful features for causal analysis, since different MACGS may include distinct workflows and organizations.

(II) Challenge of Circular Dependencies. Iterative refinement processes of MACGS may lead to circular dependencies between features, which violates the acyclicity requirement of causal graphs (see Sec. 2.2). For example, MetaGPT's implementation phase might identify missing details, prompting updates to earlier design documents.

(III) Challenge of Realistic Error Simulation. Systematically simulating realistic errors for MACGS poses two key difficulties: 1) the crafted errors should be semantically coherent within MACGS workflow, yet sufficiently different from the original output, and 2) they reflect realistic issues that could occur during agent collaborations [49].

(IV) Challenge of Limited Computation Budget. It is infeasible to exhaustively test all execution states of MACGS, since each MACGS execution incurs significant overhead [60]. Therefore, it is challenging to design an efficient exploration algorithm that can strategically make trade-offs between analysis comprehensiveness and computational overhead.

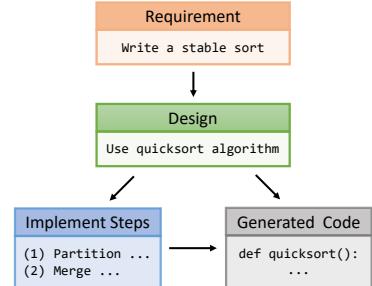


Fig. 1. Illustration of causality.

4 Methodology

This section presents CAM, an automated causality-based analysis framework for analyzing intermediate outputs in MACGS. We begin by establishing a systematic categorization method to model the complex intermediate outputs into different categories with structured semantic fields, and construct causal graph for causal analysis (Sec. 4.1). Subsequently, we simulate realistic errors of intermediate outputs through systematic counterfactuals interventions to reflect their robustness issues (Sec. 4.2). Finally, we present our automated algorithm for important feature identification and aggregate feature responsibility to measure the importance of features (Sec. 4.3).

Table 3. Categorization of Intermediate Outputs.

Category	Description	Example
Specification (3)	This category is responsible for translating the customer’s high level requirements, i.e., user queries in this context, into concrete and actionable documents like product requirement document (PRD) that guide the subsequent LLM agents in the MACGS.	Programming Language (Program_Lang)
Analysis (4)	This category focuses on systematically breaking down the specified requirements into structured analysis in the MACGS. It consolidates all identified needs, examines the problem’s objectives, and performs comparative analysis to inform the downstream agents with comprehensive understanding of what to build.	Requirement Analysis (Req_Anal)
Design (2)	This category primarily involves making architectural and algorithmic decisions that define the solution structure in the MACGS. It translates the analytical insights from previous agents into concrete implementation steps, specifying module hierarchies, data structures and function signatures.	Implementation Approach (Implement)
Dependency (3)	This category is tasked with managing external resources and inter-agent coordination in the MACGS. It identifies required external packages, specifies files to be produced, and facilitates knowledge exchange between collaborating agents to ensure coherent integration across the system.	Required Packages (Req_Pack)

4.1 Causal Modeling of Intermediate Outputs

To address the challenge of causal modeling discussed in Sec. 3.3, we propose a fine-grained categorization method that categorizes the intermediate outputs of MACGS, and systematically construct causal graph to prevent circular dependencies.

Intermediate Outputs Categorization. We leverage the output organization of MetaGPT [22] as our foundation. As a representative MACGS inspiring numerous subsequent implementations [11, 24, 38, 68], MetaGPT includes structured intermediate outputs across different agents. However, MetaGPT’s organization scheme presents two key limitations. First, the intermediate outputs of MetaGPT are organized by standard operating procedure [4] (SOP), which is not inherently reliable and may introduce biases or inconsistencies [61]. Second, this SOP-based organization lacks generalizability—MACGS with distinct architectures cannot be readily adapted to this scheme.

To overcome these limitations, we propose a function-oriented categorization method which reorganizes the intermediate outputs based on their functional roles. We systematically extract and organize four categories with 12 representative fields. As illustrated in Table 3, these categories capture distinct aspects of the code generation process, including problem context (*Specification*), requirement understanding (*Analysis*), architectural decisions (*Design*), and dependencies management (*Dependency*). While our categorization is grounded in MetaGPT, we emphasize that it exhibits substantial generalizability to other MACGS [11, 24, 68], which will be discussed in Sec. 9.1.

Causal Graph Construction. After modeling the intermediate outputs as semantic fields of different categories, we model each field as a feature variable and construct the causal graph. As discussed in Sec. 3.3, the iterative refinement process in MACGS introduces cycles that violate the construction of valid causal graph. To resolve this challenge, we define each feature variable based on its final value in the complete execution trace, excluding mid-stage values generated during iterative refinements. This definition captures the ultimate contribution of each feature to the final output while abstracting away the iterative refinement process. The resulting causal graph encodes the workflow dependencies in MACGS—each node in the graph corresponds to a feature variable, and edges between nodes capture the information flow across agents: an edge from feature f_i to feature f_j indicates that the output of an earlier agent (containing f_i) influences the computation of a later agent (producing f_j). This structured representation facilitates subsequent causal computation and systematic analysis of feature importance.

4.2 Realistic Error Simulation

As mentioned in Sec. 3.1, robustness of intermediate outputs is crucial for the overall reliability of MACGS. To understand the robustness of intermediate outputs, we simulate realistic errors of different features by systematically conducting counterfactual interventions. However, as discussed in Sec. 3.3, the intervened value of a feature should represent a semantically coherent but incorrect instantiation of that feature—one that an adversary might inject or that might arise from model errors. To achieve this, we first consider several straightforward approaches but find them inadequate: (1) random perturbation may break semantic coherence and produce unrealistic errors; (2) rule-based modification lacks flexibility and struggles to provide systematic interventions; (3) direct text deletion causes information loss without reflecting plausible failures.

Leveraging strong capabilities of LLMs in reflecting real-world scenarios [50, 57], we employ LLMs as counterfactual intervention engines. Specifically, given the original features generated by the MACGS, we prompt an LLM to produce modified versions that introduce realistic errors or misunderstandings while maintaining superficial plausibility. This LLM-based intervention approach offers two key advantages: (1) it generates semantically coherent interventions that remain contextually appropriate within the MACGS workflow, and (2) it adapts interventions to problem-specific contexts, producing diverse and realistic errors. To confirm the effectiveness of our LLM-based intervention approach, we manually inspect a random sample of 100 generated counterfactual interventions, confirming that 99 are semantically coherent with the original context while introducing realistic errors.

4.3 Identification of Important Features

After establishing the causal graph and counterfactuals, we now systematically identify important features through automated causal analysis. Specifically, we present an efficient algorithm leveraging influence sets, and aggregate feature responsibility to measure the relative importance of different features.

Problem Formulation. For each coding problem p that MACGS successfully solves in its original execution, our goal is to identify the important features for the success. Formally, let \mathcal{G} denote the causal graph extracted from problem p , with original values of feature nodes leading to correct code. Through systematically conducting counterfactual interventions on feature values, we seek to discover the *important features set*, denoted as $\mathcal{S}_p = \{S_1, S_2, \dots, S_k\}$. Each $S_j \in \mathcal{S}_p$ is an *important feature combination*, defined as a minimal combination of features whose simultaneous intervention leads to failure, leveraging the definition of actual cause introduced in Sec. 2.2. However, as mentioned in Sec. 3.3, it is infeasible to exhaustively test all possible combinations of features, which emphasizes the need for an efficient search algorithm.

Influence Set. Leveraging the unique error propagation properties of MACGS, we introduce the concept of *influence sets*. Unlike traditional configurable software systems [8, 53, 54, 59] where errors propagate deterministically through data dependencies, MACGS exhibit error containment properties due to their agents' ability to self-correct [10]. Consequently, errors on upstream features do not necessarily corrupt all downstream features. Therefore, measuring the actual influence of features facilitates better understanding of their importance. Given a feature combination S , we define the influence set of S as:

$$E(S) = \{f_j \in \mathcal{G} \setminus S : \text{sim}(f_j, f'_j) < \theta\} \quad (2)$$

where f_j and f'_j are the original value and the value observed after intervening on S . $\text{sim}(\cdot, \cdot)$ and θ determine whether a feature is semantically influenced. In essence, $E(S)$ represents the set of features whose semantics are influenced when S is intervened. Influence set provides two key advantages for our analysis. First, computing influence sets reflects the specific characteristics of

Algorithm 1: Computing Important Feature Set for One Coding Problem

Input: MACGS M , Problem p , Causal Graph \mathcal{G} , Max Combination Length L_{max} , Similarity Threshold θ , Maximum MACGS Executions Per Question N , Early Stop Patience k

Output: Important Feature Set S_p

```

1   $S_p \leftarrow \emptyset$  // Initialize  $S_p$ 
2  for feature  $f \in \mathcal{G}$  do
3     $result \leftarrow M_f(p)$  // Execute MACGS with intervention on  $f$ 
4    if  $result = False$  then
5       $S_p \leftarrow S_p \cup \{f\}$ ;
6    else
7       $E(\{f\}) \leftarrow \text{ComputeInfluenceSet}(\{f\}, \mathcal{G}, \theta)$  // Compute influence set of  $f$ 
8  for  $l = 2$  to  $L_{max}$  do
9     $Comb \leftarrow \text{Combinations}(\mathcal{G}, l)$ 
10   for all  $(S \in Comb \text{ and } \exists S' \in S_p \wedge S' \subseteq S)$  do
11      $Comb \leftarrow Comb \setminus S$  // Prune based on minimality of important feature combination
12    $S \leftarrow \arg \max_{S \in Comb} \hat{E}(S)$ ;
13    $result \leftarrow M_S(p)$  // Execute MACGS with intervention on  $S$ 
14   if  $result is False$  then
15     if  $\text{CheckMinimal}(S)$  then
16        $S_p \leftarrow S_p \cup \{S\}$  // Find an important feature combination
17   else
18      $E(S) \leftarrow \text{ComputeInfluenceSet}(S, \mathcal{G}, \theta)$ 
19     for all  $(S' \text{ where } S' \in \text{Combinations}(E(S), l))$  do
20        $Comb \leftarrow Comb \setminus S'$  // Prune based on property of influence set
21     if  $\text{Consecutive\_failures} \geq k$  then
22       continue // Early stop, shift to next length
23   if  $\text{Consumed\_queries} \geq N$  then
24     break // Budget exhausted
25 return  $S_p$ ;

```

different problems, facilitating analysis of diverse tasks. Second, features with larger influence sets ($|E(S)|$) potentially exert broader impact on the generation process, as intervention on them affects more downstream components, providing a useful heuristic for our search strategy.

However, computing influence sets requires actually executing interventions and observing the results, which incurs substantial computational overhead. To extend the influence sets for further interventions, we introduce *collective influence sets*. Leveraging the insight that a feature is likely to be influenced by S if it is influenced by subsets of S , we define the collective influence set of S as:

$$\hat{E}(S) = \bigcup_{S' \subseteq S} E(S') \quad (3)$$

where $E(S')$ denotes the influence set of subset S' that has been previously computed. The collective influence set $\hat{E}(S)$ approximates the influence of S without executing MACGS, which facilitates prioritized search strategies and better resource allocation.

Algorithm. Building upon influence set, we propose a novel algorithm which integrates two key components: (1) a greedy selection strategy that prioritize features with substantial influence and (2) pruning techniques that leverage the properties of important features and influence sets to reduce the unpromising search space.

As shown in Alg. 1, our algorithm takes the target MACGS M , problem p , causal graph \mathcal{G} , maximum combination length L_{max} (i.e., number of features in the combination), similarity threshold θ , maximum MACGS executions N , and early stop patience k as inputs, and outputs the important feature set \mathcal{S}_p . The algorithm explores feature combinations in order of increasing length, as shorter combinations can better reflect the importance of individual features and provide valuable guidance for identifying longer combinations. Specifically, we first initialize \mathcal{S}_p and then execute MACGS with intervention on each individual feature (lines 1–3). If the intervention on f leads to system failure, we identify it as an important feature and add it to \mathcal{S}_p (line 5). If the intervention does not result in failure (i.e., MACGS still generates correct code), we compute its influence sets for subsequent exploration (line 7). Subsequently, we iteratively explore feature combinations of increasing length from 2 to L_{max} (line 8). For each length ℓ , we first prune all combinations that include any previously discovered important feature combinations of length $\leq \ell - 1$ as a subset, since the important feature combinations are minimal by definition (lines 10–11). Then, leveraging the insight that features with substantial influence are more likely to induce system failures, we apply greedy selection strategy which prioritizes S with the largest collective influence set (line 12). If the intervention on S succeeds in inducing failure and S is confirmed as a minimal combination, we add S to \mathcal{S}_p (lines 14–16). Otherwise, we can prune not only S but also all length- ℓ feature combinations within its influence sets (lines 19–20), since intervening on S already perturbs all features in $E(S)$ transitively. Therefore, any length- ℓ feature combinations from $E(S)$ results in a less comprehensive perturbation, which cannot induce failure if S itself was insufficient. During the search process, if k consecutive interventions fail to discover new important combinations, we shift to the next length to avoid searching unpromising regions (lines 21–22). We continue the above process until we reach predefined resource constraints. This algorithm balances exploration and exploitation: the greedy selection exploits collective influence set to find promising combinations, while the pruning techniques aggressively eliminate unpromising regions to conserve computational resources.

Aggregating Feature Importance. After identifying \mathcal{S}_p for individual problems, we aggregate the results and measure the importance of each feature. Inspired by the concept of responsibility in actual causality (see Sec. 2.2), we measure the contribution of each feature to understand their importance. Leveraging the insight that shorter feature combinations indicate stronger necessity of each feature, we define the *feature responsibility* (FR) of a feature f_i as:

$$FR(f_i) = \sum_{p \in \mathcal{P}} \sum_{S \in \mathcal{S}_p, f_i \in S} \left(\frac{1}{|S|} \right)^2 \quad (4)$$

where \mathcal{P} denotes the problems set and S is an important feature combination for problem p . The squared inverse of combination length assigns substantially higher weights to features appearing in shorter combinations, thereby amplifying the distinction between features with varying degrees of importance [52]. By ranking features according to their FR, we obtain a quantitative assessment of their importance to MACGS correctness, providing insights for further analysis.

5 Experimental Setup

MACGS. We instantiate CAM on MetaGPT [22], one of the most representative and widely-adopted open-source MACGS. MetaGPT decomposes code generation process into structured stages, inspiring numerous subsequent MACGS implementations [11, 24, 38, 68]. We further demonstrate CAM’s extensibility to Self-Collab [11], PairCoder [68] and MapCoder [24], which are representative MACGS with distinct architectures, in Sec. 9.1.

Datasets. Our evaluation leverages four established code generation benchmarks: HumanEval-ET [6] (HumanEval in short), MBPP-ET [2] (MBPP in short), CoderEval [67], and CodeContest [33].

These datasets have been extensively applied in evaluating mainstream MACGS [11, 24, 35]. Specifically, HumanEval and MBPP offer well-constructed tasks, representing foundational evaluation benchmarks. CodeContest [33] features competitive programming challenges with elevated difficulty levels. CoderEval [67] is one of the latest introduced datasets, incorporating tasks extracted from real-world GitHub repositories, thus offering a realistic assessment of MAs. This selection spans classical evaluation scenarios to contemporary real-world contexts, enabling comprehensive analysis of MACGS across diverse programming environments. For computational efficiency, we use MBPP’s sanitized subset, CodeContest’s test partition, and CoderEval’s standalone-level tasks.

Backend LLMs. Current MACGS implementations employ the same backend LLM for all constituent agents. We employ three mainstream LLMs as backend: GPT-4o-mini [1], DeepSeek-Coder-V2-Instruct [74] (Deepseek in short) and Qwen-2.5-Coder-14B-Instruct [23] (Qwen in short). All these LLMs are widely adopted and demonstrate strong capabilities in code generation [14, 27, 72]. This selection covers both proprietary and open-source options, reflecting the diverse landscape of LLMs employed in contemporary MACGS implementations. We configure all models with a temperature of 0 for deterministic outputs, facilitating consistent causal analysis.

Parameters. We allocate a maximum of 100 MACGS executions per coding problem ($N = 100$) to balance comprehensiveness with computational feasibility. The maximum search length for feature combination is limited to five ($L_{max} = 5$), as longer combinations become less interpretable and actionable. For Eq. 2, We compute semantic similarity using Sentence-Transformer [47]. Following existing works [13, 48, 56], we set the similarity threshold θ to 0.5 ($\theta = 0.5$) to detect substantial semantic changes while filtering out minor variations caused by randomness. For each length ℓ , we employ an early stopping criterion that terminates exploration after 10 consecutive interventions fail to induce failures ($k = 10$), preventing exhaustive search of unpromising regions. We provide detailed justification for these parameter choices in Sec. 9.2.

6 Pilot Study: Validation of Causal Analysis

To validate the reliability and accuracy of CAM, we conduct a pilot study comparing feature importance ranking identified by CAM against manually annotated ranking.

For each setting with different dataset-LLM combination (12 in total), we randomly sample 15% of coding problems. Two experienced experts independently examine each problem, provided with the original problem description, all intermediate outputs, and the final code result. For each problem, annotators identify all features responsible for the final output failure and rank them by their impact on the final result, establishing a feature importance ranking. To mitigate the impact of subjectivity, annotators work independently to avoid bias. The quadratic weighted Cohen’s Kappa score [9] between the two annotators is 0.87, indicating substantial agreement [31]. The rankings from all sampled problems are then aggregated to produce the overall feature importance ranking.

For each setting, we evaluate the similarity of feature importance rankings between CAM and manual annotations using Kendall’s correlation coefficient [29], which measures ordinal association between two ranked lists and handles tied ranks appropriately. Table 4 presents the quantitative agreement metrics between CAM and manual annotations. The results demonstrate consistently high correlation across settings, with values ranging from 0.76 to 0.91, indicating strong agreement between CAM and human judgments. Therefore, the results produced by CAM are reliable and can be trusted for further causal analysis.

Table 4. Kendall’s correlation between CAM and human annotated results.

Dataset	GPT-4o-mini	Deepseek	Qwen
HumanEval	0.85	0.91	0.79
MBPP	0.88	0.82	0.76
Contest	0.82	0.85	0.76
CoderEval	0.82	0.85	0.82

Table 5. Feature appearance count in top-5 FR-rankings across all dataset-LLM settings.

Count	Feature	Category	Description
12	Req_Stat	Specification	Problem statement or specific task definition
12	Data_Struct	Design	Core data structures and their detailed definitions
10	Implement	Design	Technical implementation approach and algorithm design
10	Language	Specification	Natural language used for documentation
8	Program_Lang	Specification	Programming language chosen for code implementation
3	Req_Anal	Analysis	Detailed analysis and examination of requirement statements
3	Compet_Anal	Analysis	Comparative analysis of similar problems or questions
2	Req_Pack	Dependency	Required library packages and dependencies
0	Req_Pool	Analysis	Comprehensive requirement pool of requirements
0	Logic_Anal	Analysis	Breakdown of requirement logic flow
0	File_List	Dependency	Complete list of output files needed
0	Share_Know	Dependency	Common shared information across different modules

Table 6. Distribution of important feature combinations across different lengths. Values represent the percentage of combinations (%) at each length to all combinations containing the specified feature.

Feature	L-1	L-2	L-3	L-4	L-5	Feature	L-1	L-2	L-3	L-4	L-5
Req_Stat	97.1	1.6	1.3	0.0	0.0	Data_Struct	53.9	22.5	12.0	10.7	1.0
Logic_Anal	74.3	18.6	3.1	1.8	2.2	Req_Pack	46.2	46.2	1.0	2.9	3.7
Implement	65.7	15.7	4.5	6.4	7.8	Req_Anal	34.0	40.8	15.1	7.2	3.0
Share_Know	65.6	27.3	2.4	2.1	2.6	Compet_Anal	28.2	43.7	12.5	9.2	6.3
Req_Pool	63.6	23.8	3.5	4.0	5.1	Language	25.1	63.2	7.3	3.8	0.5
File_List	55.9	37.3	1.0	3.5	2.2	Program_Lang	21.2	45.6	15.6	15.3	2.4

7 Empirical Analysis

In this section, we present a comprehensive analysis of feature importance identified by CAM. Specifically, we investigate how feature importance patterns vary across different settings (RQ1), the influence of backend LLM choices (RQ2), and the impact of dataset characteristics (RQ3).

7.1 RQ1: Overall Feature Importance

We investigate the relative importance of different features by examining their FR distribution. Table 5 presents the appearance count of each feature in top-5 FR rankings across all 12 dataset-LLM combinations. From a categorical perspective, we observe a pronounced hierarchy in feature importance. *Specification* and *Design* features collectively dominate the top positions. Specifically, Req_Stat and Data_Struct both appear in top-5 rankings across all 12 settings, followed by Implement and Language with 10 appearances each. This dominance reflects an intuitive yet empirically validated result: modifications to fundamental problem characteristics and architectural decisions exert the greatest influence on final outcomes. In contrast, *Analysis* features exhibit moderate rankings, with Req_Anal and Compet_Anal appearing in only 3 settings, while *Dependency* features occupy the lowest positions, rarely or never reaching the top-5. This difference suggests that users seeking to reduce computational costs while maintaining performance may strategically prune or simplify *Analysis* and *Dependency* features, which will be discussed in Sec. 8.

We analyze the distribution across different length of important feature combinations. Table 6 presents the proportion of different combination lengths in which selected features appear. Overall, the majority of important feature combinations have length ≤ 3 , indicating that in many cases, a few critical features could determine the correctness of MACGS. Intriguingly, we uncover a previously overlooked phenomenon: *context-dependent features*—features whose importance manifests primarily through interactions with other features. For example, among all important feature combinations including Program_Lang, only 21.2% are identified when intervening on Program_Lang itself; while in the remaining 78.8% of cases, its importance emerges when simultaneously intervened with

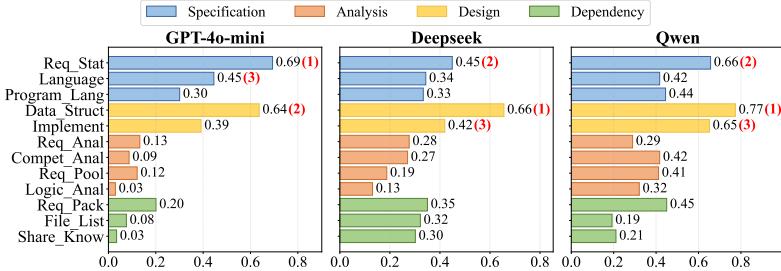


Fig. 2. Feature responsibility (FR) distribution across different LLMs on CoderEval. (1) – (3) represent top-3 FR-ranked features.

other features. This finding reveals a critical insight for improving MACGS systems: *failures arise not only from individual feature errors, but may also stem from subtle incompatibilities between seemingly correct intermediate features*. The context-dependency of Program_Lang suggests that when combined with other features (e.g., data structures), it can create semantic inconsistencies that lead to system failures—errors that would remain undetected if each feature were validated in isolation. From a practical perspective, this implies that quality assurance for MACGS should move beyond module-level validation to incorporate *cross-feature consistency checks*, ensuring that intermediate outputs are not only individually correct but also mutually compatible. This finding also validates the comprehensiveness of CAM: prior approaches [11, 24, 68] evaluating different modules solely in isolation would fail to identify such synergistic effects.

Findings: Our analysis reveals a clear hierarchy in feature importance where *Specification* and *Design* features occupy top rankings. Quality assurance for MACGS should move beyond unit-level validation to incorporate cross-feature consistency checks.

7.2 RQ2: The Influence of Backend LLM Choices

To understand the impact of backend LLMs on feature importance, we compare the FR distributions across different LLMs. Fig. 2 illustrates the FR distributions with different colors representing different feature categories. Due to space constraints, we focus on CoderEval as a representative example; similar patterns are observed across other datasets.

As shown in Fig. 2, different backend LLMs exhibit markedly distinct feature importance patterns, reflecting varying capabilities in completing feature-specific subtasks. Specifically, DeepSeek and Qwen exhibit elevated importance on *Design* features compared to GPT-4o-mini. When using DeepSeek or Qwen as the backend, Data_Struct surpasses Req_Stat in ranking; similar trends are observed across other datasets, where Data_Struct achieves FR comparable to Req_Stat. In contrast, GPT-4o-mini shows higher reliance on *Specification* features, with Req_Stat consistently ranking as most important. These distinct importance patterns reveal that different models possess varying capabilities in generating high-quality outputs for specific features, which may stems from model-specific training objectives and corpus compositions. DeepSeek and Qwen, as specialized code LLMs pretrained on extensive code repositories [19, 23], demonstrate strong capability in producing well-formed, high-quality designs, thereby enhancing their ability to solve complex programming tasks. Conversely, GPT-4o-mini, as part of the general-purpose GPT family, is trained to excel across diverse tasks by prioritizing core semantic features (e.g., requirement statements) from heterogeneous contexts. Therefore, different models prioritize different features for task completion. This suggests that optimal MACGS configurations could leverage DeepSeek and

Table 7. Pass@1 comparison of uniform and hybrid backend.

Backend LLM	HumanEval	MBPP	CodeContest	CoderEval
GPT-4o-mini (uniform)	0.7283	0.5651	0.1090	0.3492
DeepSeek (uniform)	0.6928	0.5435	0.1032	0.3326
Hybrid (GPT-4o-mini + DeepSeek)	0.7376	0.5516	0.1169	0.3676

Qwen’s superior design generation capabilities while using GPT-4o-mini’s strength in semantic feature understanding for task specification.

The observation of distinct importance patterns across LLMs motivates hybrid multi-backend architectures for MACGS, where different backend LLMs are strategically assigned to specific subtasks based on their relative strengths indicated by FR. To validate this approach, we conduct an illustrative experiment using GPT-4o-mini as the base backend, replacing only the design stage with DeepSeek to leverage its superior capability in generating high-quality designs. As shown in Table 7, this hybrid configuration outperforms both uniform backends on three out of four datasets, achieving pass@1 improvements of up to 7.2%. Intriguingly, these improvements are most pronounced on datasets requiring complex structural reasoning. Specifically, CodeContest, which demand more sophisticated algorithmic designs, benefit substantially from the hybrid approach (7.2% improvement). In contrast, MBPP—which features simpler problems that rely less on algorithm design—shows marginal degradation under the hybrid configuration. This observation aligns with our feature importance analysis: DeepSeek’s design-centric strength better serves tasks where design quality is significant for success. Furthermore, these results suggest a critical insight for MACGS optimization: *the optimal backend assignment should match model-specific feature importance patterns with stage-specific quality requirements*. Future work could explore more fine-grained assignments, such as dynamically selecting backends based on task characteristics detected at runtime. This opens a promising direction for practical MACGS optimization through systematically exploiting the complementary strengths of diverse LLMs.

Findings: Backend LLMs exhibit varying capabilities in different subtasks. The optimal backend assignment should match model-specific importance patterns with stage-specific requirements.

7.3 RQ3: The Impact of Dataset Characteristics

We analyze how problem difficulty and domain focus modulate feature importance patterns, revealing systematic variations that facilitates context-aware MACGS optimization strategies.

To comprehensively analyze importance patterns, we compute the standard deviation [55] (STD) of FR distributions to measure the uniformity of feature importance. As illustrated in Table 8, we observe that challenging datasets like CodeContest (average pass@1 10.2%) exhibit relatively uniform FR distributions across all LLMs (STD ranging from 0.1137 to 0.1773), indicating that multiple features become comparably critical. In contrast, simpler datasets like HumanEval and MBPP (average pass@1 $\geq 60\%$) display higher STD, indicating distributions with dominant high-importance features. This contrast may stem from differences in how MACGS processes problems of varying complexity. For simpler problems, MACGS relies on a small subset of critical features to derive solutions, resulting in substantially greater importance. Conversely, complex problems necessitate the synthesis of information across multiple features. Consequently, less important features provide substantial information that contributes to coding process, yielding more uniform distributions. These findings suggest that optimal resource allocation strategies should adapt to target problem difficulty. When deploying MACGS for simple tasks

Table 8. Standard deviation of FR distributions (lower is more uniform).

Dataset	GPT-4o-mini	Deepseek	Qwen
HumanEval	0.2139	0.1787	0.2121
MBPP	0.2243	0.1946	0.2226
CodeContest	0.1773	0.1137	0.1323
CoderEval	0.2216	0.1277	0.1722

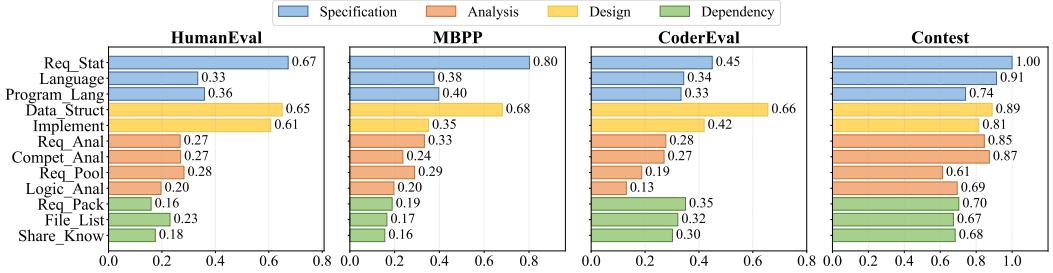


Fig. 3. Feature responsibility (FR) distribution across different datasets on Deepseek.

(e.g., basic algorithm design), users can concentrate optimization efforts on top-ranked features. For complex tasks (e.g., competitive programming), a more balanced approach that maintains quality across all feature categories becomes necessary.

We investigate how domain characteristics influence importance patterns by comparing FR distributions across different datasets. Fig. 3 presents results on Deepseek, while similar patterns emerge with other backend LLMs. Notably, we observe that task characteristics exert remarkable influence on importance patterns. In CoderEval, a dataset reflecting realistic engineering scenarios with complex module interactions and external dependencies, the importance of *Dependency* features is remarkably elevated. Specifically, *Dependency* features surpass *Analysis* features in FR ranking, demonstrating similar importance to *Specification* features. This shift aligns with the nature of engineering-oriented problems, where diverse libraries are inherently integrated, making errors in dependency resolution easily manifest as system failures. These findings suggest that practitioners applying MACGS to domain-specific tasks should prioritize optimization on corresponding features, potentially incorporating adaptive resource allocation strategies for optimized deployment.

Findings: Problem difficulty and domain characteristics modulate feature importance patterns, suggesting adaptive resource allocation strategies for optimal MACGS deployment.

8 Downstream Applications

Leveraging the FR rankings in Sec. 7, we further demonstrate two practical applications to address real-world challenges in MACGS deployment.

8.1 Causality-Guided Failure Repair

When MACGS produces incorrect code, developers face the challenge of diagnosing and correcting failures efficiently [37]. Exhaustive examination of all intermediate outputs incurs substantial human effort [42]. Our analysis suggests a causality-guided strategy: with high-FR ranked features demonstrating elevated importance to MACGS success, targeted optimization of these features may effectively resolve these failures.

We illustrate this idea by randomly sampling 15 failed cases from each dataset-LLM setting (12 in total) and systematically optimizing the top- n features according to their FR rankings. Specifically, for each sampled failure, we manually refine the top- n FR-ranked features through a three-step process: (1) comprehending the problem requirements, (2) analyzing each feature's semantic clarity and completeness, and (3) augmenting each feature with detailed interpretations and explanations. The optimized features are then reintegrated into the execution pipeline, and the resulting code is evaluated against the original test suite.

Table 9. Effectiveness of target enhancement of feature quality ($n = 3$).

Method	Pass Rate
Random-select	27.2%
Temporal-first	37.2%
Length-based	41.1%
Causality-guided	73.3%

Table 10. Impact of feature pruning on model performance across benchmarks.

Backend LLM	# Pruned	HumanEval		MBPP		CoderEval		CodeContest	
		ΔPass@1	ΔTokens	ΔPass@1	ΔTokens	ΔPass@1	ΔTokens	ΔPass@1	ΔTokens
GPT-4o-mini	2	+5.08%	-6.38%	+3.96%	-15.79%	-1.53%	-8.52%	+1.82%	-9.25%
	4	+3.63%	-25.42%	-0.67%	-21.05%	+2.06%	-31.85%	-9.09%	-22.15%
	6	+2.54%	-45.07%	-3.08%	-44.01%	-1.46%	-48.24%	-18.18%	-30.63%
	8	-4.24%	-57.98%	-2.64%	-60.91%	-3.87%	-62.52%	-36.36%	-46.84%
Deepseek	2	-2.08%	-2.36%	+2.37%	-4.18%	+0.85%	-15.68%	-7.45%	-7.50%
	4	-2.69%	-6.12%	+3.32%	-7.65%	+5.88%	-33.58%	-17.27%	-14.89%
	6	-5.21%	-39.14%	-0.08%	-43.64%	-11.76%	-47.03%	-26.36%	-28.73%
	8	-6.24%	-56.60%	-12.80%	-55.82%	-17.65%	-56.47%	-45.45%	-36.11%
Qwen	2	+0.28%	-2.88%	+1.02%	-2.31%	+5.36%	-5.53%	-9.09%	-5.87%
	4	-3.08%	-14.81%	-0.51%	-24.81%	+7.69%	-27.32%	-18.18%	-19.43%
	6	+2.02%	-37.15%	+2.54%	-43.84%	+3.77%	-35.40%	-27.27%	-32.56%
	8	-7.56%	-60.81%	-5.08%	-66.80%	-23.08%	-57.60%	-45.45%	-39.72%

To assess the applicability of the feature importance derived from CAM, we compare the causality-guided repair against three baseline strategies, including *random selection* that uniformly samples n features, *temporal-first* that prioritizes the earliest n features generated in the MACGS execution pipeline, and *length-based* that targets the n features with the greatest output length. Due to substantial manual effort, we focus on $n = 3$ to balance effectiveness with cost.

As shown in Table 9, causality-guided repair achieves an overall successful repair rate of 73.3%, significantly outperforms other baseline approaches, which only resolve 27.2%–41.1% of the failures, indicating that quality of high FR-ranked features are crucial for system correctness. These results validate CAM’s ability to identify genuinely important features. Moreover, the concentration of feature importance suggests practical failure repair: when MACGS produces incorrect code, developers should prioritize optimization of top FR-ranked features with elevated importance for system correctness, rather than exhaustively reviewing all intermediate outputs. In practice, developers can implement a hybrid workflow that combines automated validation with selective manual inspection: allocate manual review capacity exclusively to high-FR features (e.g., top-3 ranked) while accepting automated validation for lower-ranked components.

8.2 Causality-guided Feature Pruning

The computational overhead of MACGS constitutes a significant barrier to widespread adoption [22, 44]. Recent studies report that complex problems can consume hundreds of thousands of tokens across multiple agents [60]. Our causal analysis provides a new perspective for efficient MACGS deployment: if certain features exhibit low importance on system correctness, pruning these features should reduce computational costs without proportionate performance degradation.

Specifically, we systematically remove low-FR features and measure the impact on both code generation performance and computational efficiency. For each configuration, we disable the bottom- n FR-ranked features from MetaGPT execution, from $n = 2$ to $n = 8$ in increments of 2, covering a spectrum from conservative pruning to aggressive pruning. For each pruning level, we compute the relative performance change $\Delta\text{Pass}@1 = \frac{\text{Pass}@1_{\text{pruned}} - \text{Pass}@1_{\text{original}}}{\text{Pass}@1_{\text{original}}}$ and intermediate output token reduction $\Delta\text{Tokens} = \frac{\text{Tokens}_{\text{original}} - \text{Tokens}_{\text{pruned}}}{\text{Tokens}_{\text{original}}}$.

Table 10 presents the results of performance-efficiency trade-offs. We observe that conservative pruning (removing 2–4 features) not only reduces token consumption substantially but may also improve pass@1 performance. For instance, with GPT-4o-mini, pruning two features yields performance improvements across many datasets while achieving token reductions of 6.38%–15.79%, and even more aggressive 4-feature pruning maintains positive gains on HumanEval (+3.63%) and CoderEval (+2.06%). This counterintuitive improvement may be attributed to low-FR features

introducing redundant or inconsistent information that distracts MACGS from critical decision points—removing these features may enhance focus on essential reasoning pathways. However, aggressive pruning (removing 8 features) induces consistent performance degradation, confirming that high-FR features exert substantial importance. These results establish quantitative guidelines for MACGS optimization: for production deployments prioritizing cost efficiency, pruning 2–4 low-FR features achieves moderate token reduction of up to 33.6% with negligible or even positive performance impact. Moreover, CAM supports dynamic adaptive pruning strategies based on different configurations where future MACGS implementations could selectively enable or disable features based on task complexity.

9 Discussion

9.1 Generalizability and Extensibility

To demonstrate the generalizability of CAM, we instantiate CAM on another prominent MACGS, Self-Collaboration Code Generation [11] (Self-Collab in short). We further discuss the extensibility of our categorization method to PairCoder [68] and MapCoder [24].

First, as illustrated in Table 3, we map the intermediate outputs of Self-collab to different categories and features. Specifically, the *subproblems* of Self-Collab involves problem characteristics and requirement decomposition, which can be decomposed into *Specification* and *Analysis* categories. Similarly, the *high-level steps* maps to *Design* categories and the output for agent coordination maps to *Dependency* categories. Then, we execute CAM on Self-Collab. Fig. 4 demonstrates the FR distributions on representative setting. These results exhibit patterns consistent with MetaGPT while revealing architecture-specific characteristics. *Specification* features maintain dominance, with *Req_Stat* achieving the highest FR. Certain features, such as *Logic_Anal*, demonstrate elevated importance, reflecting Self-Collab’s reliance on coding logic.

Beyond Self-Collab, our categorization method readily extends to other MACGS. For example, for PairCoder [68], output for *promising plans proposal* can be mapped into *Specification* and *Analysis*, while *optimal plan selection* and *plan switch* can be decomposed into *Design* and *Dependency*. Similarly, MapCoder [24]’s diverse intermediate outputs—problem analysis, exemplar retrieval, and refinement plans—categorize into *Specification* (problem context), *Analysis* (exemplar reasoning), *Design* (coding plan), and *Dependency* (inter-agent knowledge sharing).

These analysis validate CAM’s generalizability and adaptability. Although different MACGS implementations employ different workflow structures, their intermediate outputs can be systematically aligned to our categories through appropriate semantic alignment.

9.2 Configuration of CAM

Maximum Combination Length ($L_{max} = 5$). Setting $L_{max} = 5$ balances comprehensiveness with interpretability. Table 11 presents the average contribution for each combination length to final FR. While individual features (length 1) contribute the majority of FR, combinations of length ≥ 2 contribute a significant part (19.4%), indicating that limiting analysis to the importance of individual features yields incomplete understanding. However, our experiment results show that FR values stabilize significantly and transition from length four to five produces minimal FR changes (only

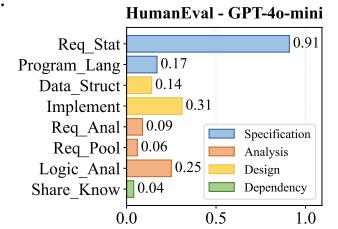


Fig. 4. Results of Self-Collab.

Table 11. Average contribution (%) for each important feature combination length to FR.

Length	1	2	3	4	5
Contribution	81.6	15.9	1.5	0.7	0.2

0.2% contribution), suggesting convergence. This configuration facilitates sound identification of important features without sacrificing interpretability through excessively complex combinations.

Early Stopping Patience ($k = 10$). The parameter $k = 10$ prevents premature termination while avoiding excessive exploration of unpromising search spaces. Table 12 presents the average number of important feature combinations identified across different k values. We observe that $k < 10$ leads to insufficient exploration, missing 21.4% combinations. For $k \in [10, 20]$, the number of identified combinations remains stable. Values $k > 20$ lead to excessive exploration of unpromising regions. Thus, $k = 10$ represents an effective balance between thoroughness and efficiency.

Table 12. Average identified combinations across different k .

k	5	10	15	20	25
# Comb	659.2	839.4	822.7	825.2	715.0

9.3 Threats to Validity

We identify and address two primary threats to validity in our paper. The first threat is the representativeness of our experimental setup. To mitigate this concern, we conduct comprehensive evaluation spanning three mainstream LLMs from different model families (proprietary and open-source), four diverse benchmarks covering various difficulty levels and domains, and demonstrate extensibility of CAM to other MACGS in Sec. 9.1. The second threat is subjectivity in manual feature importance analysis. To ensure reliability, we employ two software developers with over five years of programming experience to independently annotate feature rankings for sampled problems and resolve all disagreements.

10 Related Work

MACGS. MACGS have emerged as a promising paradigm for automated software development [5, 11, 22, 68, 69]. MetaGPT [22] is one of the most widely-adopted systems which simulates a software development team with specialized agents in distinct roles. Self-collab [11] employs three agents for planning, coding, and testing. Other systems include PairCoder [68] with clustering-based plan selection, MapCoder [24] with automated plan exploration, and CAMEL [32] with role-playing conversations. Despite their success, MACGS generate substantial intermediate outputs whose importance to the system correctness remains opaque, hindering further optimization of MACGS.

Causality Analysis in Software Engineering. Causality analysis has been extensively applied in software engineering to identify causal relationships for debugging [16] and root cause analysis [28]. Recently, formal notions of actual causality [20] have enabled precise characterization of necessary and sufficient conditions for program behaviors [3, 12, 39, 64]. However, these techniques have not been systematically applied to MACGS. We bridge this gap by presenting CAM, a causality-based analysis framework specifically designed for MACGS, which systematically quantifies the contribution of different intermediate features for system correctness.

11 Conclusion

In this paper, we present CAM, the first causality-based framework for MACGS, which identifies how intermediate outputs causally influence final code correctness. Through comprehensive experiments, we reveal critical insights including feature importance hierarchies and context-dependent causal patterns that provide actionable guidance for MACGS optimization and deployment. We demonstrate CAM’s practical utility through two applications, establishing causality analysis as a powerful approach for understanding and improving MACGS.

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