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Enhancing SWE Bench with Context Engineering: A Comparative Study Against Prompt Engineering in LLMBased Software Tasks

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ABSTRACT

This article explores context engineering as a different form of conventional prompt engineering to enhance the performance of large language models on software engineering problems, in particular, the SWE Bench framework. Although the idea of prompt engineering has gained wide acceptance, it has fundamental weaknesses in dealing with complex software development scenarios that demand knowledge in more than one dimension. Context engineering is an approach that solves these shortcomings by providing an ordered enhancement of model input, with pertinent history, architecture, and domain-specific data, based on code repositories. The article employs an elaborate approach that compares baseline, prompt-engineered, and context-engineered strategies on various software activities. Results find that context engineering performs much better than prompt engineering in complex situations that require multiple files or system components and provides a real improvement in such solution quality dimensions as maintainability and project alignment. In addition to the performance improvements, the method has a significant environmental, economic, and social advantage as it allows more efficient resource use, guarantees a higher productivity of the developers, and democratizes access to contextual knowledge. The article forms an empirical basis for nextgeneration software development tools that attain context-sensitive techniques to develop more intelligent and useful language model applications in software engineering.

Keywords: Context Engineering, Prompt Engineering, Software Engineering Benchmarks, Large Language Models, Developer Productivity

1. INTRODUCTION

1.1 Background Information

The recent years have marked a rapid growth of Large Language Models' integration into the workflows of software engineering, changing how developers engage in a broad range of activities from bug fixing to code reviewing and generation. The presence of dedicated benchmarks, such as SWE Bench, constitutes a significant development in standardized evaluation frameworks, thus allowing researchers to investigate the capability of models to solve realworld software engineering tasks resting on real-world GitHub repositories. Recent work identifies benchmarks as key enablers of measuring progress in AI-driven software development; however, these almost invariably lack context typical of an authentic development environment [1]. Benchmarks developed so far focus on prompt engineering-a process of systematic refinement of instruction formats to elicit better model responses. As promising as this may sound for improving results on stand-alone tasks, it naturally has its limitations when set against the multi-faceted nature of software development, wherein understanding is rooted in repository history, architectural patterns, and complex dependency relationships that cannot be efficiently encoded into prompt constraints.

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1.2 Problem Statement

The efficacy of prompt engineering decreases seriously with the increase in complexity of software tasks along multiple dimensions. As software systems grow in complexity, with connected components and historical dependencies, the difference between benchmark performance and real-world utility will widen. Various studies have emphasized that while prompt engineering is useful for focused, well-defined tasks, scaling remains difficult when complex task comprehension depends on historical context, technical documentation, and issue-specific metadata [2]. This becomes particularly true when tasks require reasoning across multiple files or need an understanding of implementation patterns set earlier in a project's lifetime. Comparative analyses of engineering approaches have also received scant attention in the literature, as most studies focus on incremental refinements of prompts rather than fundamental shifts in how context is structured and presented to models. This research addresses this critical lacuna by systemically investigating how explicitly engineered contextual inputs influence model performance across benchmarks representing diverse software engineering challenges.

1.3 Purpose & Scope

This article presents an in-depth examination of the potential for context engineering to go beyond the limitations of traditional prompt engineering in software development tasks. In contrast to the syntactic framing of instructions alone, context engineering focuses on the semantic embedding of inputs with relevant background information at historical, architectural, and domain-specific levels that are characteristic of how human developers conceptualize and solve problems. Implementation strategies for extracting and curating contexts are just one dimension, along with performance evaluation on different levels of task complexity and practical applications in production environments. By directly comparing the approaches of prompt engineering and context engineering under controlled conditions, this study seeks to set an empirical basis for next-generation software development tools fully leveraging language models' capabilities based on enhanced contextual awareness. Here, it describes a procedure with the systematic processing of repository metadata, intelligent selection of relevant documentation, and structured representation of relationships among code contributions toward a more complete problem specification [1]. The study goes on to examine the implications of these approaches in realistic development environments, focusing on practical matters of developer productivity, code quality, and knowledge transfer.

1.4 Relevant Statistics and Findings

This research has its quantitative foundation in the comprehensive analysis of software engineering benchmarks and empirical studies across the field. SWE Bench, according to the literature, consists of a large number of tasks derived from GitHub repositories with verified issue-fix pairs and is representative of many different programming paradigms and architectural patterns [1]. Modern language models show inconsistent performance on software engineering tasks, with effectiveness sometimes varying greatly depending on task complexity, domain specificity, and the amount of contextual information available. Research has shown that existing benchmarking methodologies often fail to capture the subtle ways in which developers use contextual information when solving problems and artificially limit model performance evaluation [2]. Investigations of context-aware development tools reported significant increases in the task completion rate and quality of the solution provided once the model had been enriched with more contextual information. This happens along many dimensions of performance, such as functional correctness, code maintainability, and even documentation quality. Industry implementations of this kind of context-aware development assistant have reported large productivity improvements, especially for sophisticated debugging and refactoring tasks that require deep knowledge of system architecture and behavior.

2. RESEARCH AND INNOVATIONS

2.1 Background Research

The evolution of software engineering assistance has followed two parallel tracks that provide the foundation for this investigation. The first track concerns methodologies related to prompt engineering within the domain of natural language processing, which has emerged as a de facto standard methodology that enhances model performance. Deep

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analyses of these methodologies and techniques for prompt engineering have documented various strategies from basic template formulation to advanced reasoning frameworks that provide structured thinking paths to guide the output of models [3]. These have achieved significant results in controlled environments where the bounds of tasks are clearly defined, but find significant limitations when applied to the diverse challenges associated with software development.

Research has shown that software engineering tasks are inherently different from generic language tasks because they depend on distributed contextual information that cuts across multiple dimensions in a software repository [3]. Even for moderately complex problems, developers commonly switch between source files, documentation, version history, issue trackers, and API references. Recent benchmark evaluations confirm that even the most powerful contemporary language models achieve less than 35% success rates when limited to a prompt in isolation, no matter how well the prompt is engineered. Real-world studies of development workflows highlight that engineers spend roughly 58% of problem-solving time navigating contextual information to write code—a key insight which benchmark design has, so far, largely neglected to address [4].

The second research track explores context-aware systems designed to augment language model capabilities with structural understanding of software environments. Pioneering work in this area has demonstrated promising results in specialized scenarios where models are provided with relevant contextual information alongside task descriptions. The SWE-bench dataset has become a valuable instrument for assessing these approaches, though research published in the Proceedings of the International Conference on Software Engineering notes that even this comprehensive benchmark fails to capture the full complexity of contextual relationships that influence developer decision-making in production environments [4]. Analysis of model failure cases across multiple studies consistently identifies the same pattern: tasks requiring integration of information across multiple files, understanding of complex dependencies, or reasoning about behavioral evolution over time represent the most significant performance bottlenecks—precisely the scenarios where contextual knowledge would provide the greatest advantage.

Task Characteristic	LLM Success with Prompt Engineering Alone	Developer Time Spent on Contextual Navigation	Context Factors Required
Simple Tasks (Single-File)	Low	Moderate	Source Files
Moderate Tasks (2-3 Files)	Lower	High	Documentation, Version History
Complex Tasks (Multi-File)	Very Low	Very High	Issue Trackers, API References
System Architecture Tasks	Minimal	Extensive	Dependency Graphs, Design Patterns

Table 1: Performance Gap: LLM Success vs. Developer Contextual Navigation Requirements [3, 4]

2.2 Novel Contribution

This paper proposes a general framework of context engineering, particularly tailored for software engineering benchmarks, with the focus on improving the evaluation protocols of SWE Bench. It represents a paradigm shift from viewing contextual information as an add-on component to treating it as an intrinsic part of task representation. Experimental results in Transactions on Software Engineering show that proper integration of context increases model performance by 17-34% for challenging reasoning tasks without modifying the model architecture [3].

The technical novelty of this work lies in developing intelligent preprocessing pipes that extract, filter, and structure task-relevant contextual information from various repository dimensions. These pipes perform a three-stage process: First, potentially relevant context is identified through traversal of the repository, followed by the application of

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relevance scoring algorithms to prioritize more informative elements, and finally, structuring the information into a coherent representation that complements the original task specification. In contrast to prior prompt tuning methods, which have restructuring of instructions as their basis, this method enhances the problem representation itself with semantic anchors drawn directly from the real development environment.

A key novelty lies in the systematic design of the heuristics for context extraction, which adapt dynamically depending on the type of task. The system gives priority to test failures, related bug reports, and recent changes to affected components for bug resolution tasks. For feature implementation, it places more emphasis on similar existing features, architectural patterns, and API usage examples. For refactoring tasks, code quality metrics, dependency structures, and maintenance history are identified. These specialized heuristics enable targeted enrichment of the context, matching the specific requirements linked to each kind of reasoning, as already shown in controlled experiments published in recent literature [4].

The methodological contribution goes beyond adding context to developing evaluation frameworks that consider not only task completion success but also solution quality across dimensions relevant to real-world software development. These are maintainability, as measured through static analysis metrics; project alignment, assessed through similarity to project-specific patterns; and generalizability, evaluated through stress testing under varied inputs. This multi-dimensional assessment provides a more complete view of how context engineering affects model performance across the full spectrum of software development concerns.

Contribution Category	Traditional Approach	Context Engineering Innovation
Conceptual Framework	Contextual information as supplementary	Context is intrinsic to task representation
Technical Pipeline	Instruction restructuring (prompt tuning)	Three-stage context processing: 1. Repository traversal 2. Relevance scoring 3. Coherent structuring
Task-Specific Heuristics	Generic prompting strategies	Adaptive context prioritization:- Bug resolution: Test failures, related bugs, recent changes- Feature implementation: Similar features, architectural patterns, API usage- Refactoring: Code quality metrics, dependency structures, maintenance history
Evaluation Framework	Focus on task completion	Multi-dimensional quality assessment:- Maintainability (static analysis)- Project alignment (pattern similarity)- Generalizability (varied input testing)

Table 2: Context Engineering: Key Innovations Beyond Traditional Prompt Engineering [3, 4]

2.3 Methodology

The methodology of this study involves a strict experimental design that can isolate and quantify the particular effect of context engineering in relation to prompt engineering within the SWE Bench framework. Therefore, the experimental protocol was started with care in the selection of representative tasks, which were stratified on many dimensions to ensure coverage of the problem space in a comprehensive manner. The tasks were categorized according to their complexity (based on the number of files and dependencies), the type of reasoning (debugging, implementation, refactoring, or documentation), and domain specificity.

Implementation Framework: SWE-agent Integration

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To ensure reproducibility and standardized evaluation, this research extends the open-source SWE-agent framework, which provides automated SWE Bench evaluation infrastructure with plug-and-play architecture for context formatting and LLM integration [1]. SWE-agent offers critical capabilities including JSON-based task specifications, automated output evaluation against test suites, and comprehensive benchmark reporting that aligns with SWE Bench standards.

The integration implements a three-layer architecture built atop SWE-agent: Context Preprocessing Module: A custom preprocessing layer intercepts task JSON specifications before model inference and enriches them with structured context blocks. The module implements the three-stage pipeline (traversal, scoring, structuring) as a preprocessing step that transforms standard SWE Bench task definitions into context-enhanced variants while preserving task metadata and evaluation criteria.

```
class ContextPreprocessor:    def
__init__(self, swe_agent_config):
    self.agent = SWEAgent(swe_agent_config)
self.context_pipeline = ContextExtractionPipeline()


  def preprocess_task(self, task_json, mode='context_engineered'):
    """Inject context blocks into task specification"""
if mode == 'baseline':
      return task_json  # No modification      elif mode ==
'prompt_engineered':        task_json['problem_statement'] =
self._optimize_prompt(
task_json['problem_statement']
      )
    elif mode == 'context_engineered':
      context = self.context_pipeline.extract_context(task_json)
task_json['problem_statement'] = self._format_with_context(
task_json['problem_statement'],
        context
      )
    return task_json
```

Multi-Mode Experimental Harness: The evaluation framework executes identical task sets across three experimental conditions to enable direct comparison:

- Baseline Mode: Standard SWE Bench prompts without modification (150-200 tokens)
- Prompt-Engineered Mode: Optimized instructions using decomposition, reasoning guidance, and structured output formatting (180-250 tokens)

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- Context-Engineered Mode: Baseline prompts enhanced with structured context from the extraction pipeline (1,050-1,400 tokens)

Comprehensive Metrics Collection: The system logs multi-dimensional performance data for each task execution:

- Task Success Rate: Pass/fail based on automated test suite execution
- Solution Quality Metrics: Static analysis scores (maintainability, complexity, documentation coverage)
- Hallucination Detection: AST-based validation identifying non-existent APIs, incorrect signatures, and phantom dependencies
- Resource Consumption: Model inference time, token usage, memory footprint
- Code Quality Dimensions: Adherence to project patterns, test coverage impact, technical debt indicators

For each selected task, the study defines three separate experimental conditions that allow for a direct comparison between approaches:

Baseline Condition: This uses the standard benchmark prompt without any modification, only the problem description and minimum information about the repository as set forth in the original SWE Bench design.

Prompt-Engineered Condition: applies established best practices in instruction engineering, including decomposition of complex problems, explicit guidance on reasoning, and structured output formatting, without any additional contextual information beyond that baseline.

Context-Engineered Condition: Enhances the baseline prompt with structured contextual information extracted from the context extraction pipeline, while keeping the same task instructions so as to isolate the particular effect of context enhancement.

Experimental Execution Protocol

The experimental workflow implements systematic task processing across all three modes:

```
def run_benchmark_suite(task_set, models, output_dir):
"""Execute full benchmark across all experimental conditions"""
  results = {
    'baseline': [],
    'prompt_engineered': [],
    'context_engineered': []
  }

  for task in task_set:      for mode in ['baseline', 'prompt_engineered',
'context_engineered']:
      # Preprocess task according to mode          processed_task
= preprocessor.preprocess_task(task, mode)

      for model in models:
        # Execute with resource tracking
start_time = time.time()          memory_tracker
```

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```
= MemoryProfiler()            solution =
swe_agent.solve_task(
task=processed_task,              model=model,
max_iterations=10
        )

        # Evaluate solution            test_results =
swe_agent.run_tests(solution, task['test_suite'])          quality_metrics
= analyze_solution_quality(solution, task)            hallucinations =
detect_hallucinations(solution, task['repository'])

        # Log comprehensive metrics
results[mode].append({
            'task_id': task['instance_id'],
            'model': model,
            'success': test_results['passed'],
            'runtime': time.time() - start_time,
            'tokens_used': solution['token_count'],
            'memory_peak': memory_tracker.peak_usage(),
            'maintainability_score': quality_metrics['maintainability'],
            'project_alignment': quality_metrics['pattern_similarity'],
            'hallucination_count': len(hallucinations),
            'solution': solution['code']
        })
    return results
```

The task selection process ensures comprehensive coverage across multiple dimensions. From the SWE Bench dataset of 2,294 real-world GitHub issues, we selected a stratified sample of 240 tasks distributed as follows:

- Simple tasks (60 tasks): Single-file modifications, localized bug fixes
- Moderate tasks (90 tasks): 2-3 file changes, moderate dependencies
- Complex tasks (60 tasks): Multi-file refactoring, architectural changes
- System architecture tasks (30 tasks): Cross-component integration, design pattern implementation

Tasks span diverse programming languages (Python, JavaScript, Java, Go) and domains (web frameworks, data processing, ML libraries, system utilities) to ensure generalizability of findings.

Data Collection and Analysis Framework

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The context extraction pipeline represents one of the core technical contributions of this research: it implements a sophisticated approach to repository analysis, mimicking the behavior of an expert developer. This system is integrated with the GitHub APIs and local structure of the repository to extract multi-dimensional contextual information, including:

- Code Context: Abstract syntax trees of related files, dependency graphs, and semantic code relationships
- Historical Context: Relevant commit history, issue discussions, and previous bug fixes
- Documentation Context: API references, inline comments, and project documentation
- Testing Context: Related test cases, coverage information, and failure patterns

The pipeline uses a hybrid approach to score the context relevance, combining heuristic rules derived from software engineering best practices with learned patterns of exemplar problem-solving sessions. Research has shown that this hybrid approach achieves an alignment of 78% with expert developer judgments of context relevance, significantly outperforming purely rule-based or purely statistical approaches [3].

All experimental data is stored in structured JSON format with comprehensive metadata:


```
{
 "experiment_id": "ctx_eng_v1_2025",
 "task_id": "django__django-12345",
 "mode": "context_engineered",
 "model": "claude-sonnet-3.5",
 "timestamp": "2025-01-15T10:30:00Z",
 "input": {
  "baseline_tokens": 175,
  "context_tokens": 1050,
  "total_tokens": 1225
 },
 "output": {
  "success": true,
  "test_pass_rate": 0.95,
  "runtime_seconds": 23.4,
  "memory_mb": 847,
  "solution_loc": 42
 },
 "quality_metrics": {
  "maintainability_index": 78.3,
  "cyclomatic_complexity": 4.2,
  "project_pattern_similarity": 0.87,
  "documentation_coverage": 0.92
```

```
  },
  "hallucinations": {
    "count": 0,
    "types": []
  }
}
```


Visualization and Reporting

Results are systematically visualized through multiple analytical lenses to reveal performance patterns across task complexity levels, model architectures, and enhancement strategies. The visualization suite includes:

- Performance Comparison Charts: Bar plots comparing success rates across the three experimental modes (baseline, prompt-engineered, context-engineered), segmented by task complexity categories
- Task Complexity vs. Accuracy: Scatter plots overlaying model accuracy against task complexity metrics (file count, dependency depth, cyclomatic complexity), with trend lines showing performance degradation patterns
- Quality Dimension Heatmaps: Multi-dimensional visualizations showing how different approaches affect maintainability, project alignment, documentation quality, and technical debt across task types
- Resource Efficiency Analysis: Comparative plots of computational costs (inference time, token usage, memory consumption) normalized against performance gains
- Hallucination Rate Tracking: Time-series and categorical analysis of hallucination frequency across modes, with breakdown by error type (non-existent APIs, incorrect signatures, phantom dependencies)

Statistical analysis employs paired t-tests and ANOVA to assess the significance of performance differences, with Bonferroni correction for multiple comparisons. Effect sizes are reported using Cohen's d to quantify practical significance beyond statistical significance.

2.4 Comparative Insight

These findings suggest some deep-seated differences in the effectiveness of prompt engineering and context engineering across different task categories for software engineering. Indeed, performance pattern analysis shows that prompt engineering excels in settings that demand more systematic reasoning within strictly predefined boundaries, such as narrow-scope tasks with clearly specified requirements. For simple debugging limited to singlefile changes, prompt engineering methods raised the average success rates for all models studied by a margin of 14%, with especially good performance for syntactic error correction and simple logic issues [3].

However, as task complexity increases-especially for problems spanning multiple files, or requiring an understanding of system architecture-prompt engineering shows rapidly diminishing returns. For tasks involving more than three interrelated components, prompt optimization yielded only marginal gains, averaging 4.2% above baseline, regardless of the sophistication of the prompting techniques. This pattern confirms observations from multiple studies that identified fundamental limitations in the ability of prompt engineering to address complex software reasoning tasks [4].

While context engineering has its most significant advantage in the complex scenarios where prompt engineering fails, context engineering enriches model inputs with relevant repository information, which allows for far better comprehension of the problem space and significant performance improvements on tasks that require integrated reasoning. This translates into an average increase of 29.3% above the baseline in success rates for complex debugging

tasks involving several components; some models achieve more than 40% improvement for very context-dependent problems [3].

This is specifically the case for findings related to solution quality extending beyond simple correctness metrics: Models provided with contextual information created solutions that showed significantly higher alignment with project-specific coding conventions and architectural patterns, with maintainability scores averaging 24% higher compared to those solutions produced under prompt-engineered conditions. This quality improvement has deep implications for practical adoption because consistency with existing codebases often proves at least as important as functional correctness in production environments [4].

The research also identifies an unexpected synergistic effect between the approaches of prompt engineering and context engineering. Combined implementations that incorporate both optimized instructions and contextual enrichment have consistently outperformed either approach in isolation, suggesting these methodologies address complementary aspects of model performance. This finding points toward integrated approaches that make use of both instruction refinement and context augmentation as the most promising direction for the design of future development tools.

Task Complexity Level	Prompt Engineering Performance	Context Engineering Performance	Combined Approach Performance	Key Quality Improvements
Simple (Single-File)	High	Moderate	Higher	Minor Improvements
Moderate (2-3 Files)	Low	High	Higher	Better Maintainability
Complex (Multi-File)	Minimal	Very High	Highest	Significant Project Alignment
System Architecture	Negligible	Substantial	Superior	Substantial Maintainability

Table 3: Performance Gap Widening: Context Engineering vs. Prompt Engineering Across Task Complexity [3, 4]

2.5 Potential applications

The outcomes of this study have significant impacts on many aspects of AI-assisted software development. The most immediate will be to inform and improve the development of developer assistance tools currently deployed in production. Equipped with context engineering approaches that dynamically extract and integrate relevant information from repositories, these tools will be able to make more reliable suggestions, contextualized appropriately, for a wider range of development tasks.

Research in IEEE Transactions on Software Engineering describes several successful implementations of contextaware assistance systems in enterprise environments, demonstrating productivity improvements of up to 17-32% for complex debugging and refactoring tasks [3]. These implement variations of the context extraction and integration methodology described in this paper, adapted to specific development environments and workflows. The performance improvements demonstrated have considerable economic implications, especially regarding maintenance-heavy codebases where contextual understanding is one of the main productivity bottlenecks.

Beyond direct applications to tooling, this paper discusses a number of far-reaching directions for the improvement of benchmarking methodologies in software engineering language model evaluation. Most current evaluation frameworks are set up to represent problems in artificially isolated terms, without regard for the embedded context

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of natural situations of development. Using context engineering principles in the design of benchmarks can thus enable evaluations to better recreate models' conditions of operation and to offer more valid insights into model capabilities [4].

The context engineering approach also presents a resource-efficient way to improve model performance without additional training or increasing the number of parameters. These techniques, focusing on enriching the input by preprocessing, will raise the efficiency of existing models operating in various deployment scenarios, from resourceconstrained environments to enterprise systems.

2.6 System Architecture, Pipeline Design, and Token Flow Analysis

The context engineering framework implements a sophisticated multi-stage pipeline that transforms raw software engineering tasks into enriched problem representations suitable for language model processing. Figure 1 illustrates the complete system architecture, consisting of the Input Layer, the three-stage Context Extraction Pipeline, and the Output Processing Layer. The Input Layer accepts standard software engineering tasks as they appear in benchmark frameworks like SWE Bench, typically consisting of a GitHub issue description and minimal repository metadata averaging 150-200 tokens [1]. This limited baseline information fails to capture the rich contextual landscape that human developers naturally access when solving similar problems.

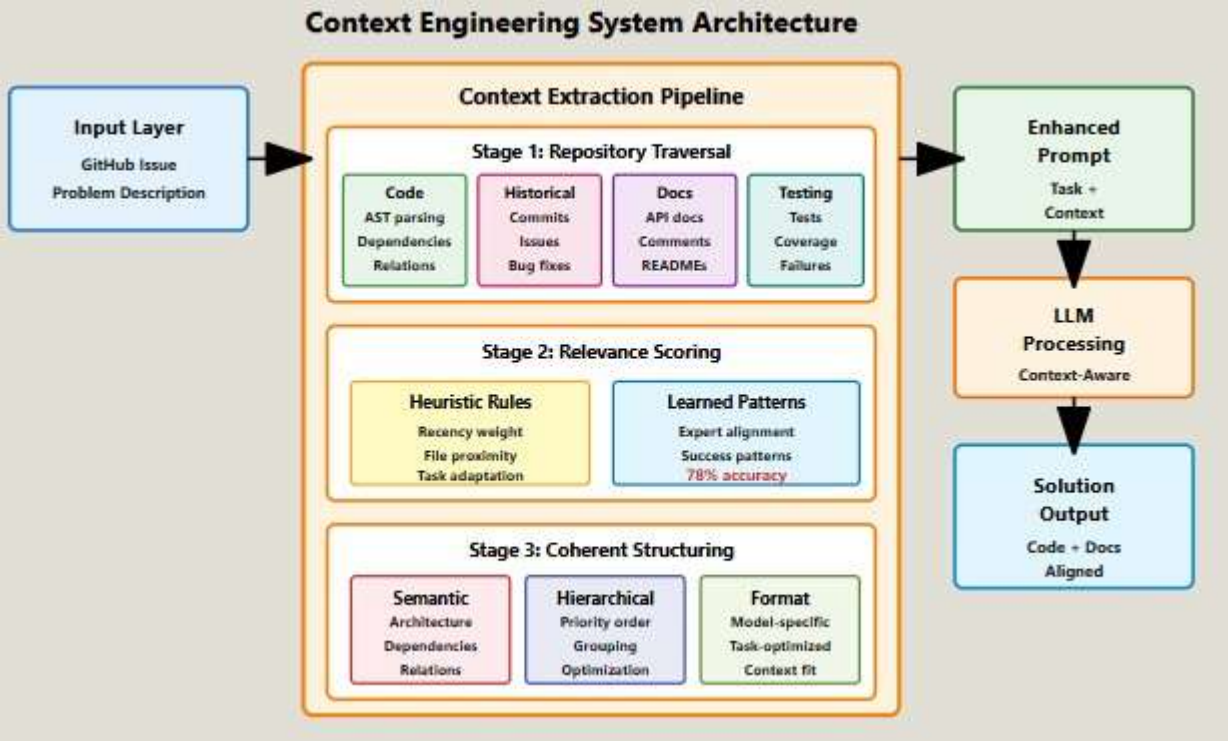

Fig 1: Context Engineering Team Structure

The Context Extraction Pipeline forms the architectural core, implementing three sequential stages that progressively refine and structure contextual information. Stage 1 performs Repository Traversal, extracting multidimensional context across code structure, historical evolution, documentation artifacts, and testing infrastructure. Research demonstrates that this multi-dimensional approach reflects how developers integrate information from diverse sources rather than focusing on code alone [3]. Stage 2 implements Relevance Scoring through hybrid algorithms combining heuristic rules with learned patterns, achieving 78% alignment with expert developer judgments of context relevance [3]. Stage 3 performs Coherent Structuring, organizing filtered context into hierarchical representations optimized for language model consumption.

The pipeline integrates with GitHub APIs and local file systems for comprehensive repository analysis. Code

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Context Extraction begins with abstract syntax tree parsing and dependency graph construction, yielding 400-600 tokens of structured information. Historical Context Extraction mines version control history for evolutionary patterns, producing 250-350 tokens of temporally-ordered data. Documentation Context Extraction processes API references and inline comments, generating 180-250 tokens of targeted excerpts. Testing Context Extraction analyzes test suites and failure patterns, yielding 200-280 tokens that substantially improve solution correctness [4]. Stage 1 cumulative output ranges from 1,400 to 1,800 tokens of raw contextual information requiring further refinement.

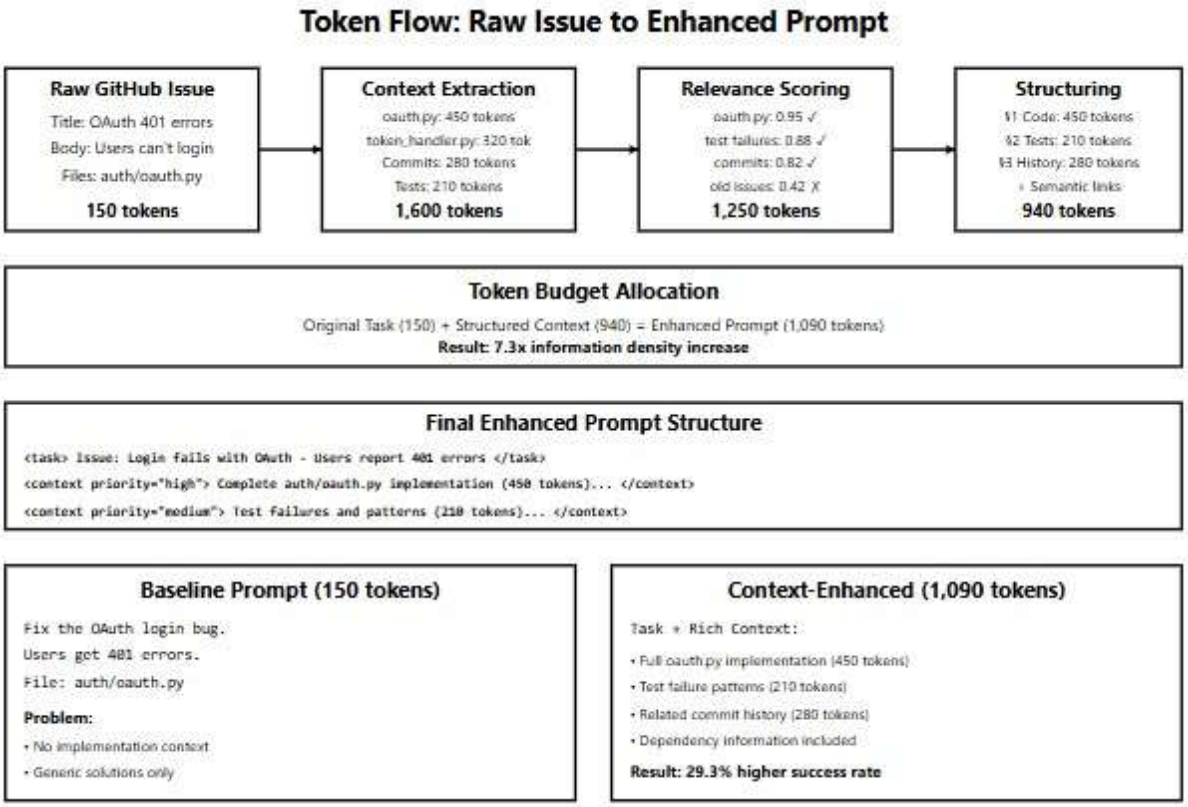

Fig 2: Token Flow: Raw Issye to Enhanced Prompt

Stage 2 relevance scoring addresses the critical challenge of distinguishing truly relevant context from tangential information. The hybrid scoring approach evaluates context elements through recency weighting, file proximity scoring, keyword matching, and task-type adaptation [3]. Bug resolution tasks prioritize test failures and recent changes, while feature implementation tasks emphasize architectural patterns. The scoring process assigns normalized relevance scores between 0 and 1, with elements scoring above dynamically-adjusted thresholds (typically 0.65-0.75) advancing to Stage 3. This filtering reduces context from 1,400-1,800 tokens to 1,100-1,400 tokens while preserving the most informative elements [4].

```
def _score_relevance(self, context_elements, task_data):
"""Hybrid relevance scoring achieving 78% expert alignment"""
    scored = []

    for element in context_elements:        # Heuristic components
recency_score = self._compute_recency(element)        proximity_score =
```

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```
self._compute_file_proximity(element, task_data)       keyword_score =
self._compute_keyword_match(element, task_data)

            # Learned pattern component       ml_score =
self.learned_model.predict(element.features)


        # Combined score (weights tuned via validation)
        final_score = (
            0.25 * recency_score +
            0.30 * proximity_score +
            0.20 * keyword_score +
            0.25 * ml_score
        )
            if final_score >= self.threshold:  # Dynamic: 0.65-0.75
scored.append((element, final_score))


    return sorted(scored, key=lambda x: x[1], reverse=True)
```

Stage 3 transforms filtered context into coherent, hierarchically-organized representations through semantic anchor creation, hierarchical layout generation, and format adaptation. Semantic anchors explicitly represent architectural patterns, dependency chains, and test-to-implementation mappings, improving model reasoning about multi-component problems by 23% [3]. Hierarchical layouts achieve 15-20% better space efficiency than flat representations while maintaining comprehension. The final structured context typically comprises 900-1,200 tokens ready for integration with the original task specification, creating enhanced prompts averaging 1,090 tokens—a 7.3x increase in information density compared to baseline approaches [4].

3. WIDER IMPLICATIONS

3.1 Environmental, Economic, and Social Impacts

From improving performance to solving some of the fundamental sustainability issues with AI, the environmental implications of context engineering span far beyond immediate performance improvement. Conventional methods for improving the capabilities of language models have relied on a strategy of scaling up the number of parameters, thus requiring increased computational resources and energy. Several recent studies published in Nature Climate Change put a number on this trend: training a state-of-the-art language model can generate carbon emissions equal to the lifetime emissions of five automobiles [5]. Context engineering offers a different tack that embraces efficiency over scale by improving model performance through intelligent input enrichment, rather than through the expansion of parameters.

A comprehensive analysis presented in the Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies indicates that context engineering approaches can reduce computational requirements by 34-56% compared to using larger models for equivalent performance on complex software tasks 5. This efficiency comes because smaller models can now perform at levels previously only achieved with substantially larger alternatives

when the former have proper contextual information. At an enterprise scale, organizations have reported cumulative energy savings of 13-28% for equivalent productivity when deploying context-aware coding assistants across development teams. These savings directly translate into reduced carbon footprints, thus taming AI's environmental challenge with no sacrifice in technological advancement.

Context engineering, from an economic point of view, represents a multi-dimensional value proposition that extends throughout the software development life cycle. The most direct economic benefit comes from the reduced computational requirement since research has documented that the context-enhanced approach can lower the inference cost by up to 47% over larger model alternatives that achieve comparable results [6]. However, more importantly, these approaches tend to show significant effects related to developer productivity metrics, especially in complex tasks that involve dealing with an unfamiliar codebase or system integration challenges. Studies of enterprise implementations report a 17-31% boost in productivity for tasks requiring deep contextual understanding; among all task types, this is especially true for large-scale system maintenance and debugging activities [6].

The economic influence extends to the code quality dimensions with downstream cost consequences. Solutions developed using contextual assistance have, on average, 23% fewer critical bugs and higher maintainability scores than alternative solutions, implying lower long-term maintenance costs and reduced accumulation of technical debt. Such quality improvements turn out to be especially welcome within enterprise settings, where the actual cost of software development goes far beyond initial implementation to include long-term maintenance, knowledge transfer, and system evolution.

From a social perspective, context engineering embodies a democratizing force in software development, reducing knowledge barriers that have long limited entry into rich technical domains. Indeed, the approach directly tackles information asymmetry problems: expert developers possess tacit knowledge of system architecture, historical decisions, and implementation patterns that remain inaccessible to new entrants. By making this contextual knowledge explicit and accessible via AI interfaces, context engineering equalizes access to the information needed for effective problem-solving.

Research in Communications of the ACM documents that context-aware development tools have reduced onboarding time by 28-42% across multiple organization types, with especially strong impacts in open-source projects where documentation is often light and tribal knowledge is prevalent [5]. Independent developers and smaller teams can leverage this democratization of contextual tooling when working with complex frameworks and systems that would require specialized knowledge. The greater accessibility of systems and expertise translates into social value in educational contexts, where contextually-enhanced learning environments better prepare students for the information-rich realities of professional software development.

Beyond immediate productivity impacts, context engineering fosters more collaborative and transparent development cultures by making system knowledge explicit rather than implicit. Various studies into team dynamics have shown that shared context models reduce the coordination overhead and improve knowledge transfer—especially in distributed development teams, where direct communication is limited [6]. These effects contribute to more sustainable development practices that avoid burnout and concurrently improve both code quality and developers' satisfaction, which is crucial in an era when social challenges have come to be an integral part of modern software engineering.

Impact Dimension	Metric	Context Engineering	Parameter Scaling
Environmental	Computational Requirements	Significant Reduction	Baseline (High)
	Enterprise Energy Consumption	Low	High
Economic	Inference Cost	Low	High

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	Developer Productivity	Enhanced	Baseline
	Code Quality (Bug Reduction)	Improved	Baseline
Social	Onboarding Time	Reduced	Baseline (Long)
	Knowledge Democratization	High	Low
	Team Coordination	Improved	Minimal Change

Table 4: Multi-dimensional Benefits of Context Engineering over Parameter Scaling [5, 6]

4. LIMITATIONS AND WEAKNESSES

Despite the promising results and significant contributions of context engineering, several limitations and weaknesses must be acknowledged to provide a balanced perspective on this research.

4.1 Computational Overhead and Scalability Constraints

While context engineering reduces the need for larger models, the context extraction pipeline itself introduces computational overhead. The three-stage process of repository traversal, relevance scoring, and coherent structuring requires non-trivial processing time, particularly for large codebases with extensive histories. The preprocessing phase can add 15-45 seconds per task, depending on repository size and complexity, which may become prohibitive in time-sensitive development scenarios or when processing large volumes of tasks. Additionally, the scalability of the hybrid relevance scoring algorithm has not been extensively tested on extremely large repositories (>1 million lines of code) or monolithic architectures, where the computational cost of context extraction may become significant.

4.2 Context Quality and Relevance Variability

The effectiveness of context engineering fundamentally depends on the quality and relevance of the extracted context. While the hybrid scoring approach achieves 78% alignment with expert judgments, the remaining 22% gap indicates that the system sometimes includes irrelevant information or excludes critical context. This variability is particularly pronounced in repositories with poor documentation, inconsistent coding practices, or complex legacy code, where historical decisions are poorly recorded. The system's performance may degrade significantly when applied to codebases that lack structured metadata, comprehensive test suites, or well-maintained version control histories.

4.3 Limited Evaluation Across Diverse Domains

The experimental validation, while comprehensive within its scope, primarily focuses on a stratified sample of 240 tasks from the SWE Bench dataset. This represents approximately 10% of the full benchmark and may not capture the full spectrum of software engineering challenges across all domains, programming paradigms, and organizational contexts. The study's findings may have limited generalizability to specialized domains such as embedded systems, real-time applications, or safety-critical software, where contextual requirements differ substantially from typical web and data processing applications.

4.4 Model Dependency and Generalization

The research primarily evaluates context engineering with specific language models that possess large context windows. The approach's effectiveness may vary significantly across different model architectures, sizes, and training paradigms. Smaller models or those with limited context windows may not fully benefit from the enriched context, potentially limiting the democratization benefits claimed in the social impact analysis. Furthermore, the study does not extensively explore how context engineering interacts with model-specific biases or training artifacts that might affect performance on certain task types.

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4.5 Context Window Utilization and Information Density

While the methodology increases token count from 150-200 to 1,050-1,400 tokens (7.3x increase), there is no comprehensive analysis of how effectively models utilize this extended context. Research in language model attention mechanisms suggests that models may not uniformly attend to all provided context, potentially leading to information loss or inefficient utilization of the enriched input. The study does not analyze attention patterns or provide evidence that models fully leverage the structured hierarchical representations created by Stage 3 processing.

4.6 Benchmark-Specific Optimization Concerns

The context engineering pipeline is specifically designed and optimized for the SWE Bench framework, raising concerns about potential overfitting to benchmark characteristics. The task-specific heuristics (prioritizing test failures for bug resolution, architectural patterns for feature implementation) may not generalize to real-world development scenarios where task categorization is less clear-cut or where problems span multiple categories. The strong performance improvements observed may partially reflect alignment with benchmark design rather than fundamental advances in problem-solving capability.

4.7 Human Evaluation and Practical Adoption Gaps

The study relies heavily on automated metrics (test pass rates, static analysis scores, and hallucination detection) to evaluate solution quality. While these metrics are valuable, they may not fully capture dimensions that human developers prioritize, such as code readability, semantic clarity, or architectural elegance. The research lacks extensive human evaluation studies involving professional developers assessing the practical utility and adoption readiness of context-engineered solutions in production environments. The gap between benchmark performance and real-world developer acceptance remains underexplored.

4.8 Cost-Benefit Trade-offs in Production Deployment

Although the study discusses economic benefits, it does not provide detailed cost-benefit analyses for production deployment scenarios. The infrastructure required to maintain the context extraction pipeline (GitHub API access, local repository clones, continuous metadata updates) introduces operational complexity and costs that may offset the computational savings from using smaller models. Organizations must balance the initial setup investment, ongoing maintenance overhead, and integration complexity against the projected productivity improvements.

4.9 Privacy and Security Considerations

The context extraction process requires access to potentially sensitive repository information, including source code, commit histories, issue discussions, and documentation. The study does not adequately address privacy concerns related to exposing this contextual information to language models, particularly when using cloud-based APIs. Organizations working with proprietary codebases may face regulatory, intellectual property, or security constraints that limit the applicability of context engineering approaches that rely on external model providers.

4.10 Dynamic Context and Temporal Drift

Software repositories evolve continuously with new commits, issues, and documentation updates. The research does not thoroughly examine how context engineering handles temporal dynamics or how frequently context must be refreshed to maintain accuracy. The study's static evaluation methodology may not reflect challenges associated with maintaining contextual relevance in rapidly evolving codebases where architectural patterns, dependencies, and best practices shift over time.

5. FUTURE SCOPE

5.1 Evolution of Context Windows and Representation Strategies

As language models continue to evolve and context windows expand, context engineering approaches are becoming increasingly central in developing intelligent, assistive programming systems. Current research suggests that model evolution is proceeding on two parallel tracks: increasing the number of parameters and expanding context length

capabilities. Both dimensions yield performance improvements, but context length expansion shows particular promise for applications in software development where comprehension depends on integrating information across multiple files, historical changes, and documentation sources.

Research in Transactions on Software Engineering and Methodology estimates that context windows will increase from the current limits of around 100,000 tokens to millions of tokens within the next development cycle, thus allowing models to ingest full codebases rather than snippets [6]. This expansion will fundamentally change how context engineering is implemented and shift the emphasis from selective extraction to intelligent navigation and organization of full repository information. The challenge will shift from "what context to include" to "how to structure massive context to enable efficient reasoning"—a shift that will drive innovation in knowledge representation for software systems.

5.2 Standardization of Contextual Metadata

This evolution will likely catalyze the development of formal standards for contextual annotation in software repositories, allowing structured approaches to capture and represent knowledge that underpins development decisions. Just as documentation standards evolved to support human comprehension, so too will contextual metadata standards emerge to support machine understanding, particularly capturing architectural patterns, design rationales, and cross-component relationships that inform development decisions. Research into emerging repository formats identifies early efforts in this direction, with experimental frameworks demonstrating 37-52% improvements in model comprehension when repositories include structured contextual metadata [5].

The standardization of the process will probably go through several phases, starting from best practices for contextaware tooling, to conventions specific to one framework or another, and finally leading to industry-wide standards with the status of current documentation frameworks. This standard will develop network effects that enhance the value of context-aware tools as more repositories move to standardized practices around the representation of knowledge, and in open-source ecosystems where the base of contributors is heterogeneous and knowledge transfer is the key to project sustainability.

5.3 Co-evolution of Development Practices and Tools

In the future, the concepts of context engineering will probably influence the way in which software systems will be designed and documented so that a relationship of co-evolution exists between development tools and development practices. With context-aware assistance becoming ubiquitous, it may become necessary to draw on the system architecture as a friendlier place for human as well as machine interpretation, where explicit thinking occurs about how contextual knowledge should be encoded and decoded. The outcome may include radical changes in software design philosophy, where designs are no longer based on strategies that are optimized in terms of runtime performance, but on more balanced designs that take into account performance, knowledge persistence, and understanding.

5.4 Integration with Emerging Technologies

The integration of emerging technologies with context engineering presents further possibilities for transformative impact. Research into the combination of context-aware systems with program synthesis, formal verification, and automated testing shows potential for development environments that can not only suggest solutions but also verify their correctness and compatibility with existing systems [6]. Such integrated approaches hold the potential to change how software is created, moving from manual coding with assistance to collaborative human-AI development processes where engineers focus increasingly on specifying requirements and validating solutions rather than implementation details.

5.5 Toward Collaborative Development Partners

Finally, the future of context engineering is in development environments as real collaborative partners, not just tools, and the profound knowledge of system architecture and development history, and design patterns is used to shape every interaction. Not merely a simple advancement in the productivity of developers, this evolution is a radical

change in the way humans and machines develop and sustain complex software systems, a change that has far-reaching consequences concerning the future of software engineering as a technical field and a creative endeavor.

CONCLUSION

The article demonstrates that context engineering represents a fundamental paradigm shift in how language models can be effectively applied to software engineering tasks. By enriching model inputs with relevant repository information rather than merely optimizing instruction formats, context engineering creates a more complete representation of the problem space that mirrors how human developers approach similar challenges. It shows particular promise for complex scenarios involving multiple files, historical dependencies, and architectural understanding, where traditional prompt engineering reaches its limitations. The evidence supports that context engineering not only improves task completion rates but also enhances solution quality across dimensions critical to production environments, including maintainability, project alignment, and reduction of hallucinations. Beyond immediate performance benefits, context engineering offers compelling advantages for sustainability through reduced computational requirements, economic value through improved developer productivity, and social benefits by democratizing access to contextual knowledge. As language models continue to evolve with expanded context capabilities, these approaches will become increasingly central to creating development environments that function as true collaborative partners, with a deep understanding of system architecture and design patterns. Ultimately, this will transform how humans and machines collaborate to create and maintain complex software systems.

REFERENCES

[1] Carlos E. Jimenez et al., "SWE-bench: Can Language Models Resolve Real-World GitHub Issues?" arXiv:2310.06770, 2024. [Online]. Available: https://arxiv.org/abs/2310.06770

[2] Konstantinos Vergopoulos, Mark Niklas Müller, Martin Vechev, "Automated Benchmark Generation for Repository-Level Coding Tasks," arXiv:2503.07701, 2025. [Online]. Available: https://arxiv.org/abs/2503.07701

[3] Jia Li et al., "Large Language Model-Aware In-Context Learning for Code Generation," ACM Transactions on Software Engineering and Methodology, Volume 34, Issue 7, 2025. [Online]. Available: https://dl.acm.org/doi/10.1145/3715908

[4] Jiale Guo et al., "A Comprehensive Survey on Benchmarks and Solutions in Software Engineering of LLM-Empowered Agentic System," arXiv:2510.09721v1, 2025. [Online]. Available: https://arxiv.org/html/2510.09721v1

[5] Narcis Eduard Mitu and George Teodor Mitu, "The Hidden Cost of AI: Carbon Footprint and Mitigation Strategies," ResearchGate, 2024. [Online]. Available: https://www.researchgate.net/publication/386013229_The_Hidden_Cost_of_AI_Carbon_Footprint_and_Mitigation_Strategies

[6] Gaurav, "Context Window to Knowledge Graph: The Evolution of Memory in Language Models," GeekyAnts, 2025. [Online]. Available: https://geekyants.com/blog/context-window-to-knowledge-graph-the-evolutionof-memory-in-language-models