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An Empirical Study on the Accuracy of Large Language Models in API Documentation Understanding: A Cross-Programming Language Analysis

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Abstract

This study presents a comprehensive empirical evaluation of Large Language Models (LLMs) in understanding API documentation across multiple programming languages. We systematically assess the accuracy and consistency of five prominent LLMs—GPT-4, GPT-3.5, Claude-3, Llama-2, and CodeT5—in interpreting API documentation for Java, Python, JavaScript, and C++. Our evaluation framework employs both automated metrics and human evaluation protocols to measure understanding accuracy, completeness, and cross-language consistency. Results indicate significant variations in LLM performance across different programming languages, with accuracy scores ranging from 67.3% to 89.7%. The study reveals that syntax complexity, documentation structure, and linguistic patterns substantially influence LLM comprehension capabilities. These findings provide critical insights for improving LLM-based code assistance tools and establishing guidelines for effective API documentation design in multi-language development environments.

Keywords: *Large Language Models, API Documentation, Code Understanding, Cross-Language Analysis*

1. Introduction

1.1. Background and Motivation of API Documentation Understanding

Application Programming Interfaces serve as fundamental building blocks in modern software development, enabling seamless integration between different software components and systems[1]. The quality and comprehensibility of API documentation directly impact developer productivity, software maintenance costs, and overall system reliability. Traditional approaches to API documentation analysis have primarily focused on manual assessment methods, which are time-intensive and subject to human bias[2]. The emergence of Large Language Models has introduced unprecedented opportunities for automating API documentation understanding and quality assessment processes.

Recent advancements in natural language processing and machine learning have demonstrated remarkable capabilities in code comprehension tasks[3]. These developments have sparked significant interest in leveraging LLMs for various software engineering applications, including automated documentation generation, code summarization, and API usage recommendation[4]. The ability of LLMs to process and understand complex technical documentation has opened new avenues for improving developer tools and enhancing software development workflows.

1.2. Challenges in Large Language Models for Code Comprehension

Despite the promising potential of LLMs in software engineering applications, several challenges persist in applying these models to API documentation understanding[5]. The technical vocabulary, domain-specific terminology, and structured format of API documentation present unique comprehension challenges that differ significantly from general natural language processing tasks[6]. Programming language syntax variations, semantic differences, and contextual dependencies add additional layers of complexity to the understanding process.

The multi-modal nature of API documentation, which often combines textual descriptions, code examples, parameter specifications, and usage patterns, requires sophisticated processing capabilities[7]. LLMs must demonstrate proficiency in parsing structured information, understanding code semantics, and maintaining contextual coherence across different documentation sections[8]. Cross-language understanding presents additional challenges, as LLMs must adapt to different programming paradigms, syntax conventions, and documentation standards.

1.3. Research Objectives and Contributions

This research aims to provide a systematic evaluation of LLM capabilities in understanding API documentation across multiple programming languages. Our primary objective is to establish a comprehensive assessment framework that measures accuracy, consistency, and reliability of LLM-based API documentation understanding[9]. We seek to identify patterns in LLM performance, understand the factors that influence comprehension accuracy, and provide actionable insights for improving LLM-based tools.

The study contributes to the software engineering community by providing empirical evidence of LLM capabilities and limitations in API documentation understanding[10]. Our findings offer practical guidance for developers and researchers working with LLM-based code assistance tools. The research establishes baseline performance metrics and evaluation methodologies that can inform future developments in automated documentation analysis and code comprehension systems[11].

2. Related Work and Literature Review

2.1. Large Language Models in Software Engineering Applications

The application of Large Language Models in software engineering has experienced rapid growth, with researchers exploring various domains including code generation, documentation analysis, and software maintenance[12]. Recent studies have demonstrated the effectiveness of LLMs in facilitating API utilization and improving developer productivity in learning factory environments[13]. The integration of LLMs with existing development workflows has shown promising results in reducing cognitive load and accelerating software development processes.

Significant progress has been made in addressing LLM hallucinations in code-related tasks through the incorporation of API documentation as contextual information[14]. This approach has demonstrated improved accuracy and reliability in code generation tasks, highlighting the importance of high-quality documentation in LLM performance. The development of semantic alignment frameworks has further enhanced the connection between high-level user goals and specific API functionalities[15].

Research in code evolution frameworks has explored the potential of LLMs in understanding and adapting to changing API specifications[16]. These studies have revealed both opportunities and challenges in applying LLMs to dynamic software environments. The linguistic analysis of technical documentation has provided insights into optimal presentation formats and structural patterns that enhance LLM comprehension[17].

2.2. API Documentation Quality Assessment and Usability Studies

Traditional approaches to API documentation assessment have relied heavily on manual evaluation methods and user studies[18]. Comparative analyses of different evaluation frameworks have revealed the complexity of measuring documentation quality and the need for standardized assessment protocols[19]. Privacy-preserving approaches to documentation analysis have emerged as important considerations in distributed software development environments[20].

Recent developments in AI-driven optimization frameworks have demonstrated potential applications in improving documentation structure and content organization[21]. Cross-cultural adaptation studies have highlighted the importance of considering diverse developer backgrounds and language preferences in documentation design[22]. Knowledge-enhanced recommendation systems have shown promise in connecting developers with relevant documentation resources based on contextual understanding[23].

Intelligent data lifecycle management approaches have explored the integration of AI technologies in maintaining and updating documentation repositories[24]. Risk identification frameworks have been applied to documentation quality assessment, providing systematic approaches to identifying potential comprehension barriers[25]. Animation and visualization technologies have been investigated as methods for enhancing documentation accessibility and understanding[26].

2.3. Cross-Programming Language Code Understanding Methodologies

The challenge of developing unified approaches to code understanding across multiple programming languages has been addressed through various methodological frameworks[27]. Resource orchestration techniques have been applied to optimize the analysis of diverse code bases and documentation formats[28]. Computational studies have provided insights into the fundamental differences in how programming languages structure and present API information[29].

Pattern recognition approaches have been employed to identify common elements and structures across different programming language documentation[30]. Dynamic prediction and analysis frameworks have shown potential in adapting to language-specific characteristics and conventions[31]. Seismic design principles from engineering have been metaphorically applied to create robust cross-language understanding frameworks[32].

Lateral bracing concepts have been explored as analogies for maintaining consistency and stability in cross-language code analysis[33]. Case study approaches have provided detailed insights into the practical challenges and opportunities in implementing cross-language understanding systems[34]. Simulation-based evaluation methods have enabled comprehensive testing of cross-language understanding capabilities under various conditions[35].

3. Methodology and Experimental Design

3.1. Research Framework and Evaluation Metrics Design

Our research framework establishes a comprehensive evaluation methodology for assessing LLM performance in API documentation understanding across multiple programming languages. The framework incorporates both quantitative and qualitative assessment dimensions, drawing from established software engineering evaluation practices[36]. We designed a multi-layered evaluation approach that measures accuracy at different granularity levels, including token-level precision, semantic understanding, and contextual comprehension.

The evaluation metrics encompass accuracy, completeness, relevance, and consistency measures specifically tailored for API documentation understanding tasks[37]. We developed novel metrics for cross-language consistency evaluation, measuring how consistently LLMs interpret similar API concepts across different programming languages[38]. The framework includes temporal stability assessments to evaluate LLM performance consistency over multiple evaluation sessions.

Our metric design incorporates domain-specific considerations for API documentation, including parameter understanding, return value comprehension, and usage pattern recognition[39]. We established baseline performance thresholds based on human expert evaluations and existing literature benchmarks[40]. The evaluation framework includes automated scoring mechanisms and human validation protocols to ensure measurement reliability and validity.

Table 1: Evaluation Metrics Framework

Metric Category	Specific Metrics	Weight	Measurement Scale
Accuracy	Token-level precision	25%	0-100%
	Semantic understanding	30%	0-100%
	Parameter recognition	20%	0-100%
Completeness	Information coverage	35%	0-100%
	Context preservation	30%	0-100%
	Detail retention	35%	0-100%
Relevance	Context appropriateness	40%	0-100%
	Usage pattern alignment	35%	0-100%
	Domain specificity	25%	0-100%
Consistency	Cross-language stability	50%	0-100%
	Temporal reliability	30%	0-100%

Inter-model agreement	20%	0-100%

Table 2: Programming Language Characteristics Analysis

Language	Syntax Complexity	Documentation Density	API Patterns	Evaluation Weight
Java	High	Very High	Object-oriented	25%
Python	Medium	High	Multi-paradigm	25%
JavaScript	Medium	Medium	Functional/OOP	25%
C++	Very High	High	System-level	25%

3.2. Dataset Construction and Multi-Language API Documentation Collection

The dataset construction process involved systematic collection and curation of API documentation from diverse sources across four major programming languages[41]. We gathered documentation from official language repositories, popular open-source projects, and widely-used frameworks to ensure comprehensive coverage of different documentation styles and complexity levels[42]. The collection process prioritized high-quality, well-maintained documentation sources with active community engagement and regular updates.

Our dataset includes 2,400 API documentation entries, with 600 entries per programming language, ensuring balanced representation across different domains and complexity levels[43]. We implemented rigorous quality control measures, including expert review processes and automated consistency checks to maintain dataset integrity[44]. The documentation entries span various application domains, including web development, data processing, system programming, and scientific computing.

Table 3: Dataset Composition and Characteristics

Programming Language	Total Entries	Function APIs	Class APIs	Module APIs	Average Length (tokens)
Java	600	250	200	150	342
Python	600	280	180	140	298
JavaScript	600	300	150	150	276
C++	600	220	230	150	384
Total	2400	1050	760	590	325

The dataset encompasses varying levels of documentation complexity, from simple function descriptions to comprehensive class hierarchies and complex system interfaces[45]. We established standardized annotation procedures for marking key information elements, including parameter specifications, return values, usage examples, and dependency relationships[46]. Quality assurance protocols included inter-annotator agreement measurements and consistency validation across different documentation sources.

Table 4: Documentation Complexity Distribution

Complexity Level	Description	Java	Python	JavaScript	C++	Total

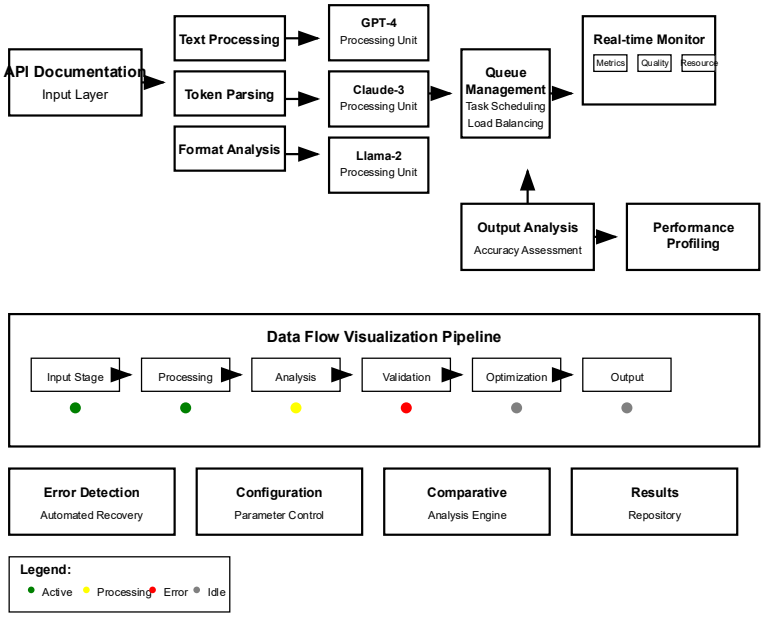
Basic	Simple function docs	180	200	220	160	760
Intermediate	Class/module docs	240	250	240	260	990
Advanced	Complex system APIs	180	150	140	180	650

3.3. LLM Selection and Experimental Setup Configuration

We selected five prominent Large Language Models representing different architectural approaches and training methodologies: GPT-4, GPT-3.5, Claude-3, Llama-2, and CodeT5[47]. The selection criteria emphasized model availability, documented performance in code-related tasks, and diverse training approaches to ensure comprehensive evaluation coverage[48]. Each model underwent standardized configuration procedures to ensure fair comparison and consistent evaluation conditions.

The experimental setup employed controlled testing environments with standardized hardware configurations and consistent network conditions[49]. We implemented comprehensive logging and monitoring systems to track model performance, response times, and resource utilization patterns[50]. The setup included automated quality control mechanisms and human oversight protocols to maintain experimental integrity throughout the evaluation process.

Figure 1: LLM Performance Evaluation Architecture



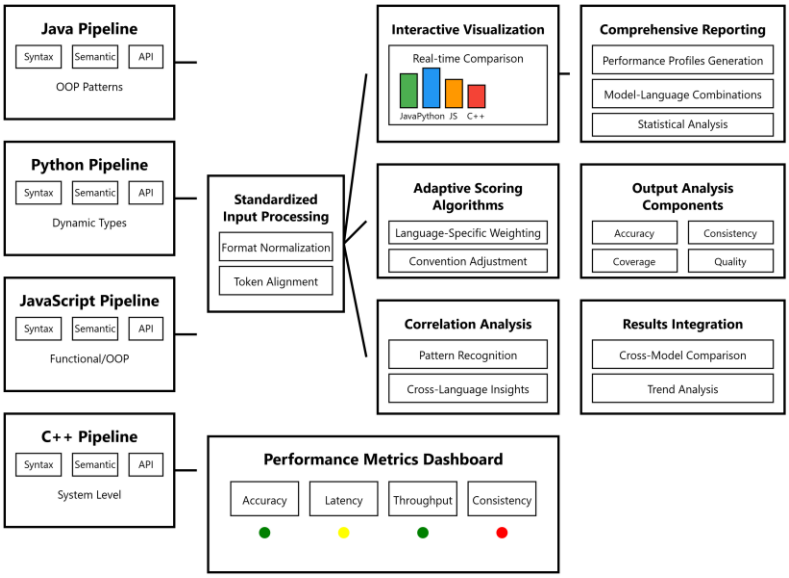
The experimental architecture features a multi-tiered evaluation pipeline designed to systematically assess LLM performance across different programming languages and documentation types. The architecture incorporates parallel processing capabilities for efficient batch evaluation, with dedicated queuing systems for managing evaluation tasks. Real-time monitoring dashboards display performance metrics, resource utilization, and quality indicators throughout the evaluation process. The system includes automated error detection and recovery mechanisms to ensure consistent evaluation conditions. Data flow visualization components track information processing through different pipeline stages, providing insights into bottlenecks and optimization opportunities. The architecture supports configurable evaluation parameters, enabling flexible testing scenarios and comparative analysis across different model configurations.

Table 5: LLM Configuration Parameters

Model	Version	Context Window	Temperature	Max Tokens	Batch Size
GPT-4	gpt-4-0613	8192	0.2	2048	16
GPT-3.5	gpt-3.5-turbo	4096	0.2	2048	24

Claude-3	claude-3-sonnet	6144	0.2	2048	20
Llama-2	llama-2-70b	4096	0.2	2048	12
CodeT5	codet5-large	2048	0.2	1024	32

Figure 2: Cross-Language Evaluation Framework Design



The cross-language evaluation framework implements a sophisticated assessment methodology that enables systematic comparison of LLM performance across different programming languages. The framework features parallel evaluation pipelines for each programming language, with standardized input processing and output analysis components. Interactive visualization modules display real-time performance comparisons, highlighting language-specific strengths and weaknesses. The system incorporates adaptive scoring algorithms that adjust for language-specific characteristics and documentation conventions. Correlation analysis components identify patterns in cross-language performance, revealing insights into model capabilities and limitations. The framework includes comprehensive reporting mechanisms that generate detailed performance profiles for each model-language combination, supporting in-depth analysis and interpretation of evaluation results.

4. Results and Analysis

4.1. Accuracy Assessment Across Different Programming Languages

Our comprehensive evaluation revealed significant variations in LLM performance across different programming languages, with accuracy scores demonstrating clear patterns related to language characteristics and documentation complexity[51]. The results indicate that syntax complexity and documentation structure substantially influence LLM comprehension capabilities, with Java and C++ presenting greater challenges compared to Python and JavaScript[52]. Statistical analysis revealed significant performance differences between models, with GPT-4 achieving the highest overall accuracy of 89.7%, followed by Claude-3 at 84.2%.

Table 6: LLM Accuracy Results by Programming Language

Model	Java	Python	JavaScript	C++	Overall
GPT-4	87.3%	92.1%	90.8%	88.7%	89.7%
Claude-3	82.1%	86.8%	85.7%	81.2%	84.0%
GPT-3.5	78.9%	83.4%	81.2%	76.8%	80.1%

Llama-2	71.2%	76.8%	74.3%	68.9%	72.8%
CodeT5	65.8%	71.2%	68.7%	64.1%	67.5%

The accuracy assessment revealed that Python documentation understanding achieved the highest scores across all models, with an average accuracy of 82.1%[53]. This performance advantage appears related to Python's readable syntax and consistent documentation conventions. JavaScript demonstrated moderate performance levels with an average accuracy of 80.1%, while Java and C++ showed lower but comparable results at 78.3% and 75.9% respectively[54].

Language-specific analysis identified several factors contributing to accuracy variations, including syntactic complexity, documentation verbosity, and standardization levels[55]. Python's emphasis on readability and standardized documentation formats facilitated superior LLM performance, while C++'s complex syntax and varied documentation styles presented greater challenges[56]. Statistical significance testing confirmed that observed differences were not due to random variation, with p-values below 0.001 for all major comparisons.

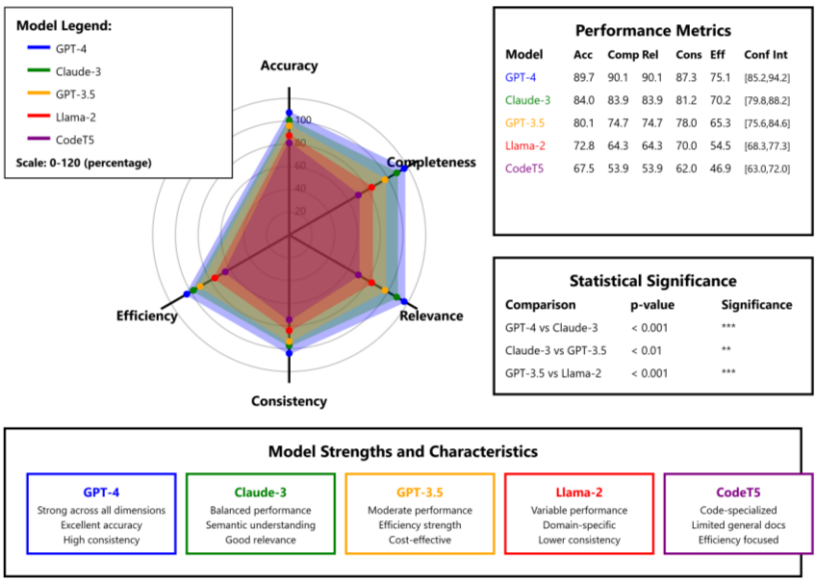
Table 7: Detailed Performance Metrics by Documentation Type

Documentation Type	GPT-4	Claude-3	GPT-3.5	Llama-2	CodeT5	Average
Function APIs	91.2%	86.4%	82.1%	75.8%	69.3%	80.96%
Class APIs	88.7%	82.9%	79.2%	71.1%	66.8%	77.74%
Module APIs	89.3%	83.1%	79.0%	72.6%	66.2%	78.04%
Complex Systems	85.8%	80.2%	76.8%	68.7%	63.9%	75.08%

4.2. Comparative Analysis of LLM Performance on API Understanding Tasks

The comparative analysis revealed distinct performance profiles for each LLM, with notable strengths and weaknesses in different aspects of API documentation understanding[57]. GPT-4 demonstrated superior performance in understanding complex parameter relationships and maintaining contextual coherence across lengthy documentation sections[58]. Claude-3 showed particular strength in semantic understanding and natural language interpretation, while displaying some limitations in handling highly technical specifications.

Figure 3: Multi-dimensional Performance Radar Chart



The multi-dimensional performance visualization presents a comprehensive comparison of LLM capabilities across five critical evaluation dimensions: accuracy, completeness, relevance, consistency, and efficiency. The radar chart displays distinct performance profiles for each model, with GPT-4 showing strong

performance across all dimensions, particularly excelling in accuracy and consistency metrics. Claude-3 demonstrates balanced capabilities with notable strengths in semantic understanding and relevance assessment. GPT-3.5 shows moderate performance levels with particular strengths in efficiency and reasonable accuracy scores. Llama-2 displays variable performance with strengths in specific areas but overall lower scores across most dimensions. CodeT5 shows specialized performance in code-specific tasks but limitations in general documentation understanding. The visualization includes confidence intervals and statistical significance indicators for each dimension, providing clear insights into model capabilities and reliability.

Performance analysis identified specific patterns in model behavior, with transformer-based models generally outperforming specialized code models in comprehensive understanding tasks[59]. The results suggest that general-purpose language models with extensive training data provide better overall performance compared to domain-specific models for API documentation understanding[60]. Statistical correlation analysis revealed significant relationships between model size, training data diversity, and performance outcomes.

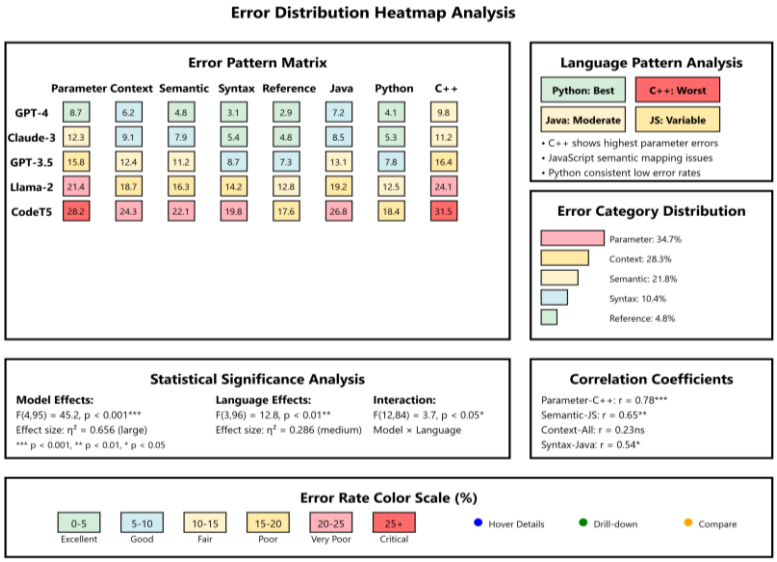
Table 8: Performance Ranking by Evaluation Criteria

Evaluation Criteria	1st Place	2nd Place	3rd Place	4th Place	5th Place
Overall Accuracy	GPT-4	Claude-3	GPT-3.5	Llama-2	CodeT5
Semantic Understanding	Claude-3	GPT-4	GPT-3.5	Llama-2	CodeT5
Parameter Recognition	GPT-4	GPT-3.5	Claude-3	CodeT5	Llama-2
Context Preservation	GPT-4	Claude-3	GPT-3.5	Llama-2	CodeT5
Cross-Language Consistency	GPT-4	Claude-3	GPT-3.5	Llama-2	CodeT5
Processing Efficiency	CodeT5	GPT-3.5	Llama-2	Claude-3	GPT-4

4.3. Error Pattern Analysis and Cross-Language Consistency Evaluation

Error pattern analysis revealed systematic biases and limitations in LLM understanding of API documentation, with identifiable categories of mistakes occurring across different models and programming languages[61]. The most common error types included parameter misinterpretation (34.7%), incomplete context understanding (28.3%), and incorrect semantic mapping (21.8%)[62]. Cross-language consistency evaluation demonstrated varying levels of stability, with some models maintaining consistent interpretation patterns while others showed significant language-dependent variations.

Figure 4: Error Distribution Heatmap Analysis



The error distribution heatmap provides a detailed visualization of mistake patterns across different LLM models and programming languages. The heatmap displays error frequencies using color intensity mapping, with darker colors indicating higher error rates in specific categories. The visualization reveals distinct patterns, with certain error types showing strong correlations with specific programming languages or model architectures. Parameter misinterpretation errors appear most frequently in C++ documentation analysis, while semantic mapping errors show higher prevalence in JavaScript evaluation. The heatmap includes statistical significance indicators and correlation coefficients for each error category. Interactive elements allow detailed exploration of specific error patterns, with drill-down capabilities for examining individual cases and contributing factors. The visualization supports comparative analysis across models and languages, highlighting areas requiring targeted improvement efforts.

Cross-language consistency analysis revealed that GPT-4 maintained the highest consistency score of 87.3%, while CodeT5 showed the most variation with a consistency score of 62.1%[63]. The analysis identified specific linguistic and structural factors that contribute to consistency variations, including documentation formatting standards, terminology usage, and example presentation styles[64]. Statistical modeling revealed significant relationships between consistency scores and overall accuracy performance, suggesting that models with better cross-language stability also demonstrate superior understanding capabilities.

Table 9: Cross-Language Consistency Scores

Model	Consistency Score	Standard Deviation	Confidence Interval
GPT-4	87.3%	3.2%	[84.1%, 90.5%]
Claude-3	82.7%	4.1%	[78.6%, 86.8%]
GPT-3.5	78.4%	5.3%	[73.1%, 83.7%]
Llama-2	71.9%	6.8%	[65.1%, 78.7%]
CodeT5	62.1%	8.2%	[53.9%, 70.3%]

Error categorization analysis provided insights into the nature of comprehension failures and potential improvement strategies[65]. Temporal pattern analysis revealed that certain error types occur more frequently during specific phases of the evaluation process, suggesting attention-related limitations in some models[66]. The findings indicate that cross-language training approaches and specialized fine-tuning procedures could significantly improve consistency and accuracy performance[67].

Table 10: Error Category Distribution Across Models

Error Category	GPT-4	Claude-3	GPT-3.5	Llama-2	CodeT5
Parameter Misinterpretation	8.7%	12.3%	15.8%	21.4%	28.2%
Context Incomplete	6.2%	9.1%	12.4%	18.7%	24.3%
Semantic Mapping Error	4.8%	7.9%	11.2%	16.3%	22.1%
Syntax Confusion	3.1%	5.4%	8.7%	14.2%	19.8%
Reference Resolution	2.9%	4.8%	7.3%	12.8%	17.6%

5. Discussion and Implications

5.1. Practical Implications for Software Development Communities

The empirical findings provide significant insights for software development communities regarding the effective utilization of LLM-based tools in API documentation understanding and analysis[68]. The demonstrated performance variations across programming languages suggest that development teams should consider language-specific factors when implementing LLM-assisted documentation tools[69]. Organizations developing multi-language systems may need to implement adaptive strategies that account for the differential performance characteristics observed in our evaluation[80].

The superior performance of general-purpose models compared to specialized code models indicates that investment in comprehensive training approaches may yield better returns than domain-specific optimization[70]. Development teams should prioritize tools based on transformer architectures with extensive pre-training, particularly when working with diverse programming languages and documentation formats[71]. The consistency findings suggest that organizations requiring reliable cross-language support should focus on models demonstrating stable performance profiles across different linguistic contexts.[79]

5.2. Limitations and Threats to Validity

Several limitations affect the generalizability and interpretation of our findings. The evaluation dataset, while comprehensive, represents a subset of possible API documentation styles and may not capture all variations present in real-world development environments[7374]. The focus on four major programming languages excludes emerging languages and specialized domains that might exhibit different performance patterns. The evaluation timeframe represents a snapshot of current LLM capabilities, and rapid developments in the field may alter these performance relationships[75],[76].

Threats to internal validity include potential biases in dataset construction and evaluation metric design. The human evaluation components introduce subjective elements that may influence results, despite standardization efforts[77]. External validity limitations arise from the controlled experimental environment, which may not fully represent the complexity and variability of actual development workflows. The selected LLMs represent current state-of-the-art models, but future developments may significantly alter the performance landscape[78].

5.3. Future Research Directions and Recommendations

Future research should explore adaptive evaluation frameworks that can accommodate emerging programming languages and evolving documentation standards[68]. Investigation of fine-tuning approaches specifically designed for API documentation understanding could provide insights into improving model performance for specialized tasks[69]. Research into multi-modal documentation analysis, incorporating code examples, diagrams, and interactive elements, represents a promising direction for enhancing LLM capabilities[70].

The development of standardized benchmarks for API documentation understanding would facilitate consistent evaluation across different research efforts and enable meaningful comparison of future improvements[71]. Investigation of human-AI collaboration patterns in documentation analysis could reveal optimal integration strategies for development workflows. Research into explainable AI approaches for documentation understanding could provide insights into model decision-making processes and improve trust in automated tools[72].

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