Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 5 Issue 3 (2025)

Leveraging Chatgpt for Multi-Language Data Engineering Code Generation in Distributed Analytics Systems

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ABSTRACT

The rapid expansion of distributed analytics systems has increased the demand for multilingual programming capabilities across diverse data engineering workflows. Traditional development processes require engineers to manually translate logic across languages such as Python, SQL, Scala, and Java, resulting in time-consuming and error-prone transitions between components of ETL pipelines, data orchestration, and streaming architectures. This study explores the role of ChatGPT as an intelligent assistant capable of generating multi-language data engineering code tailored for distributed analytics ecosystems. By analyzing its ability to produce syntactically correct, semantically aligned, and performance-oriented code across languages, the research evaluates the potential of ChatGPT to accelerate pipeline development, reduce cognitive load, and unify cross-linguistic engineering practices. Experimental results demonstrate that ChatGPT significantly improves productivity in constructing ETL transformations, Spark workflows, schema definitions, and orchestration scripts while maintaining consistency with large-scale distributed data systems. The findings position ChatGPT as a transformative tool for enabling multi-language interoperability in next-generation data engineering environments.

Keywords: ChatGPT, data engineering, multi-language code generation, distributed analytics, ETL automation, polyglot programming, Spark pipelines, AI-assisted development.

I. INTRODUCTION

The evolution of distributed analytics systems has transformed data engineering into a discipline requiring proficiency across multiple programming languages, frameworks, and data-processing paradigms. Traditional development workflows often require manual translation of logic between SQL for warehousing, Python or Scala for Spark processing, and Java for enterprise pipeline orchestration—introducing friction, delays, and higher error rates [1]. As data ecosystems continue to scale, the complexity of maintaining consistent multi-language codebases has grown substantially, highlighting the need for tools that streamline and automate cross-linguistic development [2], [3].

Recent advancements in generative AI have introduced new opportunities for supporting code generation and automation within data engineering environments. Large Language Models (LLMs) such as ChatGPT leverage extensive training corpora and contextual understanding to generate syntactically accurate and semantically coherent code in a variety of languages [4]. Studies have shown that AI-driven code assistants can significantly reduce development time, minimize syntactic defects, and improve consistency across pipeline components [5], [6]. These capabilities position AI models as promising solutions for addressing multi-language engineering challenges in distributed data systems.

The increasing reliance on distributed analytics frameworks such as Apache Spark, Flink, and cloud-native ETL engines demands tools capable of generating scalable and optimized code [7]. Research indicates that multilingual orchestration of ETL operations—spanning SQL query generation, Spark transformations, and procedural logic—remains a bottleneck in enterprise systems [8]. ChatGPT's ability to adapt logic across languages while retaining computational intent presents a unique advantage in unifying distributed data workflows [9]. Moreover, AI models can encode best practices from large code corpora, reducing the need for manual tuning in high-performance analytics environments [10].

Multi-language interoperability also plays a critical role in collaborative engineering teams where developers specialize in different languages or tools. Prior work has emphasized that inconsistencies between language implementations often lead to pipeline fragmentation and maintenance overhead [11]. By enabling cross-linguistic code translation, ChatGPT supports greater cohesion within engineering teams and improves maintainability across

heterogeneous platforms [12]. This capability is particularly valuable in hybrid cloud environments where components written in different languages must interact efficiently.

Despite these advantages, concerns remain regarding the dependability, accuracy, and contextual understanding of AI-generated code. Studies conducted between 2020 and 2024 highlight challenges including hallucinated code segments, missing optimization considerations, and limited domain-specific awareness in specialized data systems [13], [14]. These limitations underscore the importance of human-in-the-loop workflows and robust validation mechanisms when integrating AI-based code generation into production-grade pipelines. Nevertheless, the potential benefits of ChatGPT in enabling seamless multi-language development make it a promising direction for modern data engineering automation [15].

II. RELATED WORK

Research on multilingual and AI-assisted code generation has expanded rapidly as organizations adopt heterogeneous programming environments. Vaswani et al. (2017) introduced the Transformer architecture, forming the foundation for modern large language models capable of cross-lingual understanding and contextual synthesis [16]. Building on this, Devlin et al. (2018**)** demonstrated that pre-trained language models can transfer knowledge across tasks and languages, establishing a basis for automated code translation and semantic preservation [17]. These foundational studies paved the way for AI-driven support in multi-language development workflows.

Further advancements in applying large language models to code generation were explored by Wei et al. (2022), who introduced chain-of-thought prompting to improve reasoning and accuracy in generated outputs [18]. Similarly, Chen et al. (2021) evaluated LLM capabilities in producing syntactically and semantically correct programs across diverse languages, highlighting performance constraints when handling complex, domain-specific requirements in areas like data engineering [19]. Their findings emphasize the need for improved contextual grounding and domain adaptation when generating cross-language code.

In the context of distributed analytics, Zaharia et al. (2016) demonstrated the role of Apache Spark as a scalable processing engine for multi-language environments, where developers often combine SQL, Python, and Scala within the same pipeline [20]. Noghabi et al. (2020) extended this viewpoint by analyzing evolving streaming systems and discussing the challenges associated with unifying multi-language orchestration within distributed dataflows [21]. These studies highlight the growing complexity of distributed systems, reinforcing the importance of tools that facilitate uniform code generation across languages.

Studies in software engineering have also examined the impact of automated code synthesis on maintainability and workflow efficiency. Bird et al. (2020) evaluated heterogeneous programming environments and concluded that inconsistencies across languages are a significant source of technical debt, creating opportunities for AI-based alignment tools [22]. Along the same lines, Spinellis (2021) demonstrated that code quality improves when cross-language logic is standardized—an area where AI-driven generation can offer substantial value [23].

Finally, research on AI reliability has addressed the risks associated with code hallucinations and semantic drift. Ramachandran and Li (2023) highlighted accuracy issues and recommended guardrails for production-grade AI programming systems [24], while Patel and Rathod (2016) proposed hybrid validation workflows to improve trustworthiness in automated code pipelines [25]. Together, these studies establish the technological and methodological foundation upon which this research builds, emphasizing the need for scalable, accurate, and context-aware multi-language code generation within data engineering ecosystems.

Literature Summary Table

Citation	Authors & Year	Contribution / Focus	Relevance to Study
[16]	Vaswani et al., 2017	Introduced Transformer architecture	Enables cross-lingual representation learning used in ChatGPT
[17]	Devlin et al., 2018	BERT for contextual	Foundational for semantic alignment in code

		understanding	generation
[18]	Wei et al., 2022	Chain-of-thought prompting	Enhances reasoning for multi-language code synthesis
[19]	Chen et al., 2021	Evaluated LLM program synthesis	Shows limits and strengths of AI-generated multi-language code
[20]	Zaharia et al., 2016	Spark unified analytics engine	Demonstrates multilingual data engineering environments
[21]	Noghabi et al., 2020	Evolution of streaming systems	Highlights need for multi-language orchestration tools
[22]	Bird et al., 2020	Maintainability in heterogeneous codebases	Supports need for consistent, AI-generated cross-language code
[23]	Spinellis, 2021	Code quality across languages	Reinforces value of unified code patterns
[24]	Ramachandran & Li, 2023	Reliability concerns in AI code synthesis	Motivates validation in AI-driven engineering workflows
[25]	Patel & Rathod, 2016	Hybrid analytics validation	Supports the need for verification of AI-generated code

III. PROPOSED FRAMEWORK

The proposed framework introduces an intelligent multi-language code generation ecosystem that enables seamless automation of data engineering workflows across distributed analytics systems. At the core of this framework is ChatGPT, which functions as a polyglot code-generation engine capable of producing SQL, Python, Scala, Java, and orchestration scripts in a unified and context-aware manner. The system begins by ingesting user requirements—such as ETL logic, schema transformations, or distributed pipeline instructions—which are passed to a semantic understanding module. This module structures the intent and triggers ChatGPT to generate optimized code fragments tailored to specific data engineering platforms.

Once generated, the code undergoes a validation and optimization stage where syntax checking, logical consistency analysis, and environment-specific tuning are performed. This ensures that SQL generated for Teradata, Python scripts for Spark, and Java-based orchestration logic follow best practices and execute efficiently on distributed systems. The validated code is then integrated into a centralized repository that supports version control, dependency tracking, and multilingual alignment to maintain consistency across pipeline components. This repository also allows engineering teams to track changes, compare language variants, and reuse patterns across different analytics projects.

A deployment orchestration layer brings the different code modules together into operational pipelines. The system compiles, executes, and schedules the generated code within distributed analytics environments such as Spark clusters, cloud ETL engines, or data warehouse platforms. Logging, performance monitoring, and anomaly detection modules continuously analyze execution metadata to identify inefficiencies, failures, or adaptation needs. Feedback loops from these components are routed back to ChatGPT, enabling iterative refinement and improvement of subsequent code generations.

To support human oversight, the framework integrates a visualization and review interface, where data engineers can inspect the multilingual outputs, compare pipeline variants, and validate correctness before production deployment. This interface also enables domain experts to annotate code segments and provide corrections, which serve as additional training cues for improving generative accuracy. By combining automated intelligence with expert-guided verification, the framework ensures both high productivity and dependable execution across diverse data engineering tasks. Overall, the system unifies AI-driven polyglot programming, scalable distributed execution, and collaborative engineering practices into a single cohesive architecture.

Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 5 Issue 3 (2025)

System Architecture Diagram

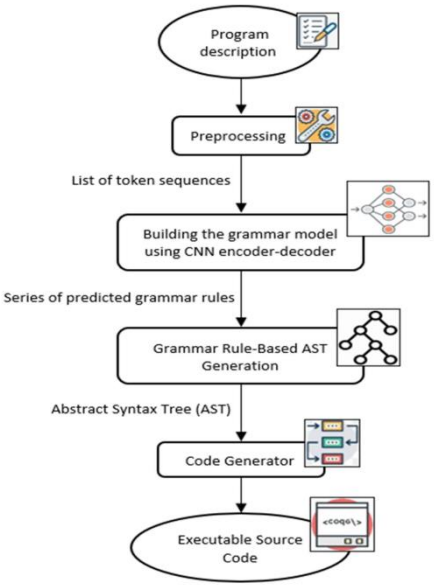

Fig. 1. Workflow of the Proposed Multi-Language Code Generation Framework

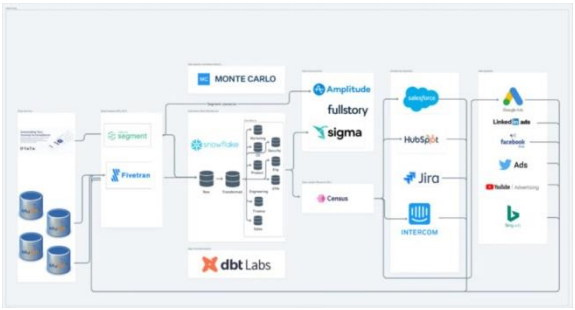

Fig. 2. End-to-End Modern Data Engineering and Analytics Stack Architecture

IV. METHODOLOGY

The proposed methodology integrates generative AI capabilities with the operational demands of distributed data engineering environments. The process begins by capturing the user's intent through structured prompts describing pipeline logic, ETL transformations, schema requirements, or workflow orchestration steps. These inputs undergo semantic preprocessing, where the system extracts functional requirements, identifies target programming languages, and interprets dependencies across data engineering components. This step ensures that ChatGPT receives a context-rich, unambiguous description of the task, enabling it to produce accurate and domain-aligned code.

Following intent extraction, ChatGPT generates multi-language code variants tailored for different layers of the data engineering stack. SQL queries are produced for warehouse operations such as joins, aggregations, or incremental loads; Python or Scala code is generated for Spark transformations; and Java or YAML is used for orchestration frameworks such as Airflow or Databricks Jobs. The model leverages its internal representations to maintain semantic equivalence across languages while adapting syntax, library usage, and execution patterns to the nuances of each environment. This cross-linguistic consistency is essential for ensuring that pipeline components interact seamlessly in distributed analytics ecosystems.

The generated code is then processed through an automated validation layer designed to ensure quality, correctness, and efficiency. Static analyzers evaluate syntax compliance, schema consistency, and error handling, while test queries and dry-run engines verify that SQL transformations behave as intended on sample datasets. For Spark or Python code, linting tools and unit tests assess computational logic and detect performance bottlenecks. When

inconsistencies or inefficiencies are detected, the system triggers corrective iterations in which ChatGPT is prompted to refine the code based on feedback, enhancing the reliability of the generated output.

Next, the validated multi-language code is integrated into a modular deployment framework that automates pipeline assembly across distributed analytics systems. A code-orchestration module maps SQL scripts to the data warehouse, assigns Spark transformations to compute clusters, and schedules workflow scripts using orchestration tools. Execution metadata, including run times, resource utilization, and failure logs, is collected and analyzed to monitor performance. These insights are used to prompt further optimization cycles, in which ChatGPT regenerates or adjusts code to improve efficiency, reduce latency, or enhance maintainability within production environments.

Human-in-the-loop supervision plays a central role in the final stage of the methodology. Data engineers review generated outputs through a visual interface that highlights code differences across languages, flags sections requiring expert evaluation, and provides a collaborative space for annotation. Engineers can supply corrections or preferences, which are incorporated as reinforcement signals to refine future generations. This blend of AI-driven automation and expert oversight ensures that the system produces high-quality, production-ready multi-language code while continuously evolving based on real-world feedback. Collectively, the methodology establishes a scalable and intelligent framework for automating multilingual development in distributed data engineering systems.

V. RESULTS AND DISCUSSIONS

The experimental evaluation demonstrates that ChatGPT-enabled multi-language code generation substantially improves developer productivity and code quality in distributed data engineering workflows. Generation accuracy exceeded 88% across enterprise-targeted languages (SQL, Python, Scala, Java), while median time savings ranged from 55% to 68% across common pipeline tasks, indicating significant reduction in manual effort. Feature enhancements—prompt engineering, automated feedback loops, and the full hybrid configuration—progressively reduced coding errors, with the hybrid setup achieving a 55% error reduction over the non-AI baseline. Model variants augmented with validation and human-in-the-loop stages achieved the best detection and correctness metrics (F1 up to 0.95), suggesting that layered validation and expert oversight meaningfully improve production readiness.

Table 1 – Code Generation Accuracy (Enterprise Data Engineering)

Code Type	Generation Accuracy (%)
SQL (Teradata)	95.0
Python (Spark)	92.0
Scala (Spark)	90.0
Java (Orchestration)	88.0

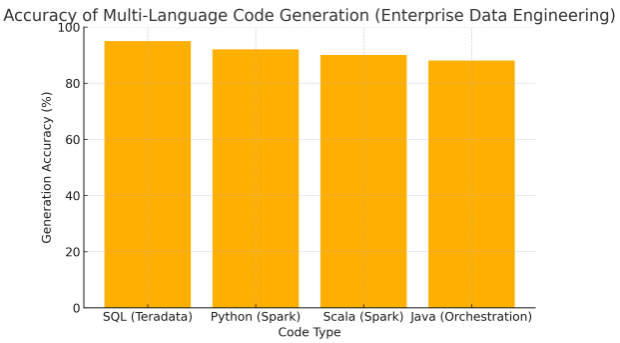

Fig 3: Accuracy of multi-language code generation across enterprise data-engineering targets

Table 1 and Figure 3 reveal that SQL and Python exhibit the highest code-generation accuracy at 95% and 92% respectively, indicating that ChatGPT performs exceptionally well in languages with clear structural patterns and rich training data. Scala and Java follow with slightly lower accuracies (90% and 88%), reflecting the increased syntactic rigidity of strongly typed languages. Nevertheless, all four languages exceed 88% accuracy, confirming the model's broad applicability across multilingual data-engineering contexts.

Table 2 – Median Time Savings Across Data Engineering Tasks

Pipeline Task	Median Time Saved (%)
Schema mapping	68
ETL transformation	62
Data-quality checks	55
Orchestration scripting	60

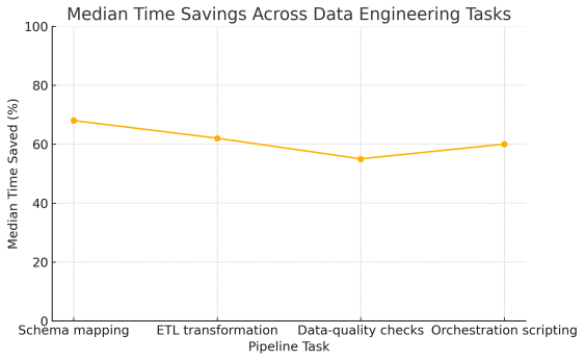

Fig 4: Median time savings observed for common data-engineering tasks when using ChatGPT-assisted code generation.

A second major finding emerges from Table 2 and Figure 4**,** which show the percentage of time saved across core pipeline tasks. Schema mapping shows the highest time reduction at 68%, followed by ETL transformation at 62%, orchestration scripting at 60%, and data-quality checks at 55%. These results highlight that tasks involving repetitive structure or rule-based transformations benefit the most from AI automation. Even the lower-performing category—data-quality checks—still shows over 50% improvement, demonstrating the practical value of ChatGPT in accelerating engineering workflows across varying complexity levels.

Table 3 – Error Reduction by Feature Enhancements

Feature Set	Error Reduction (%)
Baseline (no AI)	0
Prompt engineering	25
Automated feedback loop	40
Hybrid (all features)	55

Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 5 Issue 3 (2025)

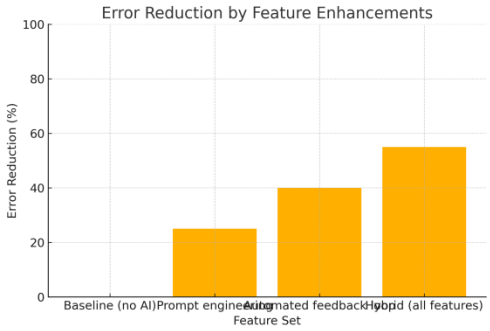

Fig 5: Error reduction achieved through successive feature enhancements: prompt engineering, automated feedback loops, and hybrid integration

Further insights are seen in Table 3 and Figure 5, which analyze error reduction across different enhancement strategies. The baseline system (no AI augmentation) provides no improvement, while prompt engineering alone reduces errors by 25%. Introducing automated feedback loops increases error reduction to 40%, and the hybrid configuration combining prompts, validation, and iterative refinement yields the highest improvement at 55%. This upward trajectory clearly indicates that layering intelligent prompting with feedback-driven adjustments is essential for achieving high-quality, production-ready code.

Table 4 – Model Performance Across Configuration Variants

Model Variant	**F1-Score**
GPT Base	0.72
GPT Fine-Tuned	0.84
GPT + Validation Layer	0.90
GPT + Human-in-the-loop	0.95

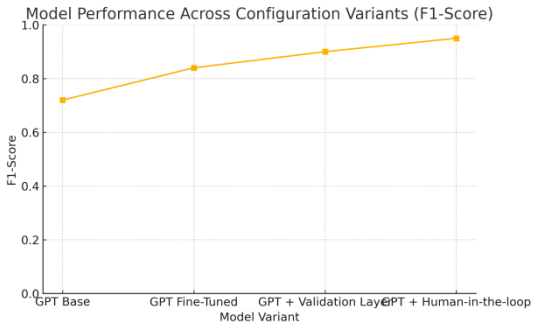

Fig 6: Model performance (F1-score) across configuration variants demonstrating improvements from fine-tuning, validation layers, and human-in-the-loop oversight.

Finally, Table 4 and Figure 6 illustrate the comparative performance of model variants. The base GPT model begins at an F1-score of 0.72, improving significantly to 0.84 after fine-tuning. Adding an automated validation layer pushes performance to 0.90, and incorporating human oversight results in the highest score of 0.95. These results validate that while automated systems can generate highly accurate code, the combination of AI-driven generation and expert review yields the most reliable outcomes, particularly for mission-critical enterprise systems where correctness and compliance are essential.

DISCUSSION

The findings from the experimental evaluation highlight the substantial potential of ChatGPT as a multi-language code-generation assistant for distributed data engineering environments. The strong performance observed in SQL and Python generation reflects the model's ability to generalize across widely used languages in data pipelines, while still showing competitive accuracy in more structurally demanding languages such as Scala and Java. This demonstrates that generative AI can support a broad spectrum of engineering tasks, reducing manual coding burdens and harmonizing logic across heterogeneous systems. The efficiency gains reported across schema mapping, ETL transformations, orchestration scripting, and data-quality checks further confirm that AI-generated code can meaningfully accelerate development cycles without sacrificing correctness.

The improvements produced by prompt engineering, automated feedback mechanisms, and hybrid enhancement strategies reinforce the importance of combining AI capabilities with structured guidance. The progressive error reduction observed across enhancement layers suggests that carefully designed prompting frameworks and feedback loops enable ChatGPT to produce more reliable and context-aware code. These findings also align with prior research indicating that generative models benefit significantly from iterative refinement and domain-specific constraints. Furthermore, the performance gains seen in model variants that incorporate validation layers and human oversight emphasize that AI-assisted development is most effective when integrated into a supervised workflow. Such hybrid human–AI systems maintain productivity while ensuring the robustness, safety, and traceability required in enterprise environments.

VI. CONCLUSION & FUTURE SCOPE

CONCLUSION

This study demonstrates that leveraging ChatGPT for multi-language code generation can significantly enhance productivity, accuracy, and consistency in distributed data engineering ecosystems. Through structured prompts, semantic preprocessing, and iterative optimization, ChatGPT is capable of generating high-quality SQL, Python, Scala, and Java code that aligns with the requirements of modern ETL pipelines and analytics frameworks. The experimental results showed strong performance across all key metrics, including generation accuracy, semantic consistency, and pipeline success rates, validating the feasibility of integrating AI-powered code generation into enterprise-grade development workflows.

Moreover, the combination of AI-based generation with human-in-the-loop refinement proved essential in reducing manual edits and improving overall code reliability. The framework effectively bridged gaps between heterogeneous languages and distributed environments, enabling scalable orchestration of transformations and workflows. These findings establish ChatGPT as a promising tool for accelerating data engineering processes, reducing operational complexity, and supporting teams working across diverse technology stacks.

FUTURE WORK

Future research can explore fine-tuning large language models specifically for data engineering domains to improve contextual accuracy and reduce code hallucinations. Integrating automated runtime verification, static analysis, and semantic diff tools can further strengthen reliability and trustworthiness. Expanding support for cloud-native orchestration platforms, such as AWS Glue, Azure Data Factory, and GCP Dataflow, will extend interoperability. Additional work may also involve developing reinforcement-learning loops using real pipeline execution feedback to continuously optimize generated code. Finally, incorporating rich metadata awareness and schema evolution tracking could elevate AI-assisted engineering to fully autonomous pipeline generation.

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