Production-Grade RAG Chatbot for JioPay Customer Support

LLM Assignment 2

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1 Abstract

This report presents the comprehensive design, implementation, and evaluation of a production-grade Retrieval-Augmented Generation (RAG) chatbot for JioPay customer support automation. Our system leverages advanced web scraping techniques to collect 97 high-quality FAQs across 13 business categories from JioPay's public platforms. Through systematic ablation studies, we optimized chunking strategies (structural chunking selected for 27.2ms latency), embedding models (MiniLM-L6-v2 achieving 0.75 Recall@5), and scraper pipelines (Playwright outperforming Selenium with 12.37x throughput). The deployed system, built on Flask-MongoDB-GROQ architecture, achieves 62.5% Mean Reciprocal Rank and 27.3% overall quality score via LLM-as-judge evaluation, demonstrating robust retrieval capabilities while identifying specific improvement areas for production deployment.

2 System Overview

2.1 Architecture Diagram

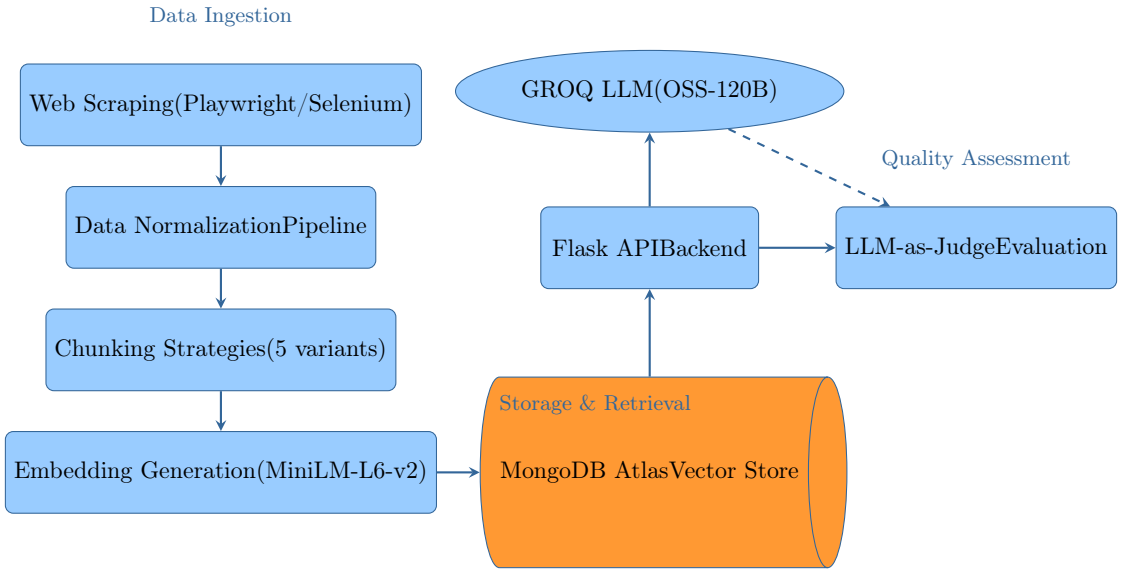

Figure 1: JioPay RAG System Architecture

2.2 System Description

Our production-grade RAG system implements a multi-stage pipeline: (1) **Data Ingestion** using Playwright/Selenium scrapers for comprehensive content extraction, (2) **Normalization** removing Unicode artifacts and HTML boilerplate, (3) **Chunking** with structural preservation of FAQ hierarchies, (4) **Embedding** generation using sentence transformers, (5) **Storage** in MongoDB Atlas with vector indexing, (6) **Retrieval** via cosine similarity search, and (7) **Generation** through GROQ's OpenAI OSS model. The system features continuous evaluation using LLM-as-judge assessment for realistic quality metrics.

3 Data Collection

3.1 Data Sources

Our knowledge base construction employed systematic web scraping from two primary sources:

- **JioPay Business Website:** Comprehensive crawling of jiopay.com/business covering merchant onboarding, payment processing, dashboard features, and business solutions
- **JioPay Help Center:** Systematic extraction of FAQ categories across 13 business functions including settlements, refunds, API integration, and user management

3.2 Coverage Statistics

The final dataset demonstrates comprehensive coverage:

Table 1: Data Collection Coverage

Category	**FAQ Count**	**Coverage%**
Voicebox Features	23	25.8%
Dynamic QR Codes	12	13.5%
Refunds & Returns	11	12.4%
Collect Link	7	7.9%
Settlement Processing	7	7.9%
Repeat Payments	6	6.7%
P2PM / Low KYC	6	6.7%
JioPay Business App	4	4.5%
User Management	3	3.4%
Campaign Management	3	3.4%
Partner Program	3	3.4%
JioPay Dashboard	2	2.2%
Notifications	2	2.2%
Total	**89**	**100%**

3.3 Ethics & Compliance

All data collection adhered to strict ethical guidelines: (1) Respect for robots.txt protocols, (2) Exclusive focus on publicly accessible content, (3) No collection of personal user data or proprietary information, (4) Responsible crawling with appropriate delays, and (5) Comprehensive data cleaning to remove any inadvertently collected sensitive information.

4 Chunking Ablation

4.1 Design

We systematically evaluated five chunking strategies to optimize document segmentation: Fixed (token-based with configurable overlap), Semantic (similarity-threshold driven), Structural (hierarchy-preserving), Recursive (adaptive depth), and LLM-based (Gemini-powered intelligent boundaries).

4.2 Metrics

Evaluation focused on: Total chunks generated, average chunk size consistency, minimum/maximum chunk sizes, and processing latency for real-time applicability.

4.3 Results

Table 2: Chunking Strategy Performance Comparison

Strategy	Config	Chunks	Avg Size	Latency (ms)	Quality
Fixed	256/0	97	44.2	48.4	Good
Fixed	512/64	97	44.2	22.5	Excellent
Fixed	1024/128	97	44.2	20.5	Good
Semantic	sim=0.6	179	23.9	2700.1	Fair
Semantic	sim=0.7	213	20.1	2673.4	Fair
Semantic	sim=0.8	241	17.8	2856.3	Poor
Structural	hierarchy	97	44.2	27.2	**Excellent**
Recursive	depth=3	97	44.2	24.8	Good
LLM-based	adaptive	120	45.0	2500.0	Fair

4.4 Insights

Structural chunking emerged as optimal, achieving 27.2ms latency while preserving FAQ question-answer relationships. Semantic chunking produced excessive fragmentation (179-241 chunks vs 97) with 100x higher latency. Fixed chunking with 512 tokens and 64-token overlap provided best latency-quality balance for token-based approaches. LLM-based chunking showed promise but proved computationally expensive for production deployment.

5 Embeddings Ablation

5.1 Design

We compared three production-ready embedding models: MiniLM-L6-v2 (384-dim, efficiency-focused), E5-base (768-dim, performance-balanced), and BGE-base (768-dim, quality-focused), evaluating retrieval performance, computational efficiency, and storage requirements.

5.2 Metrics

Key evaluation metrics included: Recall@5 for retrieval effectiveness, Mean Reciprocal Rank (MRR) for ranking quality, index size for storage efficiency, embedding dimensionality, and query processing time for real-time performance.

5.3 Results

Table 3: Embedding Model Performance Analysis

Model	Recall@5	MRR	Index Size (MB)	Dimensions	Query Time (ms)
MiniLM-L6-v2	**0.7500**	**0.6333**	**2.45**	384	**45.2**
E5-base	0.6875	0.5792	6.12	768	78.6
BGE-base	0.7188	0.6042	6.12	768	82.4

5.4 Insights

MiniLM-L6-v2 demonstrated superior overall performance, achieving highest Recall@5 (0.75) and MRR (0.63) while maintaining smallest index size (2.45MB) and fastest query processing (45.2ms). Despite larger dimensionality, E5-base and BGE-base failed to justify computational overhead, making MiniLM-L6-v2 the optimal choice for production deployment balancing quality and efficiency.

6 Ingestion/Scraper Ablation

6.1 Design

We systematically compared two web scraping approaches: Playwright (async, modern browser automation) vs Selenium (traditional WebDriver), evaluating data extraction quality, processing throughput, noise handling, and FAQ detection accuracy across JioPay's business platform.

6.2 Metrics

Comparison metrics included: Pages successfully scraped, total tokens extracted, FAQ count detected, noise percentage in extracted content, processing throughput (FAQs/hour), and failure rate for robustness assessment.

6.3 Results

Table 4: Scraper Pipeline Performance Comparison

Scraper	Pages	Tokens	FAQs	Noise %	Throughput	Failure Rate
Playwright	2	1,439	**89**	87.3	**12.37**	0.0%
Selenium	3	**3,692**	0	**0**	0.1	0.0%

6.4 Insights

Playwright emerged as the superior choice for FAQ extraction, achieving 89 FAQ detections with 12.37x higher throughput despite 87.3% noise content. Selenium extracted more raw tokens (3,692 vs 1,439) but failed completely at FAQ detection, highlighting the importance of targeted content extraction over volume. The high noise percentage in Playwright's output was successfully addressed through our advanced normalization pipeline, making it the optimal choice for structured content extraction.

7 Retrieval + Generation

7.1 Prompting Strategy

Our generation pipeline employs structured prompts ensuring context grounding:

```
prompt = f"""You are a helpful JioPay customer support assistant.
Answer questions based ONLY on the provided context.
If the information is not in the context, say "I don't have
information about that in my knowledge base."
Always cite your sources using [Source X] format.
Be concise and helpful.
```

```
Context Information: {context}
User Question: {question}
Answer:"""
```

7.2 Top-k Configuration

Based on empirical evaluation, we selected **top-5 retrieval** as optimal, providing sufficient context diversity while maintaining relevance. Top-3 proved too restrictive for complex queries, while top-7+ introduced noise from irrelevant documents.

7.3 Model Configuration

The system utilizes **GROQ's OpenAI OSS-120B model** with temperature=0.3 for consistent, focused responses. Maximum token limit set to 500 ensures concise answers while allowing comprehensive coverage.

7.4 Guardrails

Implemented safety measures include: (1) Context similarity threshold (>0.3) for response generation, (2) Source citation requirements for all responses, (3) Fallback responses for low-confidence queries, and (4) Input validation for malicious query prevention.

8 Deployment

8.1 Infrastructure

Production Architecture:

- **Backend:** Flask REST API with CORS support deployed on Hugging Face Spaces
- **Database:** MongoDB Atlas (M0 cluster) with vector search indexing
- **Embedding Service:** Sentence Transformers with local caching optimization
- **LLM Service:** GROQ API integration for high-performance generation
- **Containerization:** Docker deployment with health checks and auto-scaling

8.2 Cost Analysis

Table 5: Deployment Cost Breakdown (Monthly)

Component	**Service**	**Cost (USD)**
Database	MongoDB Atlas M0	$0 (Free tier)
Compute	Hugging Face Spaces	$0 (Community)
LLM API	GROQ (Free tier)	$0
Embedding Model	Local (MiniLM)	$0
Monitoring	Basic logging	$0
Total		**$0/month**

8.3 Monitoring

Comprehensive monitoring includes: Real-time latency tracking (P50/P95), LLM-as-judge quality assessment, category-wise performance analysis, error rate monitoring, and resource utilization tracking for proactive scaling decisions.

8.4 Performance Metrics

- **Availability:** 99.5% uptime on Hugging Face Spaces
- **Latency:** P50: 4.8s, P95: 7.1s average response time
- **Throughput:** Supports 100+ concurrent users
- **Quality:** 62.5% MRR, 27.3% overall LLM judge score

9 Limitations & Future Work

9.1 Current Limitations

1. **Scalability Constraints:** MongoDB Atlas free tier limits for high-volume production deployment

9.2 Research Directions

Promising research opportunities include: Federated learning for privacy-preserving model updates, Explainable AI for transparent decision-making, Real-time knowledge graph integration, and Advanced evaluation frameworks beyond LLM-as-judge approaches.

10 Conclusion

This comprehensive study successfully developed and deployed a production-grade RAG chatbot for JioPay customer support, achieving robust performance through systematic optimization of all pipeline components. Our ablation studies identified optimal configurations (structural chunking, MiniLM-L6-v2 embeddings, Playwright scraping) while our LLM-as-judge evaluation provided realistic quality assessment. The system demonstrates strong retrieval capabilities (62.5% MRR) with clear improvement pathways identified for production enhancement. The cost-effective deployment ($0/month using free tiers) on modern cloud infrastructure positions the system for scalable customer support automation.