LLM-Based Software Requirements Analysis Assistant

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February 7, 2026

Contents

Abstract

Software Requirements Engineering (RE) represents a foundational phase in the software development lifecycle, where the elicitation, analysis, and specification of requirements directly influence project success, cost efficiency, and system quality [8]. Despite its importance, RE is inherently susceptible to challenges such as human-induced errors, linguistic ambiguities, inconsistencies across stakeholder inputs, and redundancies that can propagate throughout subsequent development stages [4].

This thesis introduces an innovative “LLM-Based Software Requirements Analysis Assistant,” a sophisticated system leveraging Large Language Models (LLMs) to automate the identification and mitigation of these issues in natural language requirements documents [1]. The proposed assistant employs a modular architecture that integrates advanced natural language processing techniques, including semantic analysis, inconsistency detection algorithms, and redundancy elimination protocols. Key features include automated parsing of unstructured inputs, real-time flagging of vague terminology, and cross-requirement consistency checks [2].

To ensure reliability, the system incorporates a human-in-the-loop (HITL) validation framework [5]. Preliminary evaluations demonstrate the assistant’s potential to reduce RE errors by up to 40%, enhance specification clarity, and streamline collaboration [7]. Ultimately, this work contributes to advancing automated RE practices, paving the way for future integrations with emerging AI technologies.

1 Introduction

The software development lifecycle (SDLC) is a multifaceted process that begins with the critical phase of Requirements Engineering (RE), where the foundational needs and expectations of a system are elicited, analyzed, documented, and validated [8]. This phase sets the trajectory for all subsequent activities. In an era dominated by complex, large-scale software systems, the quality of requirements directly correlates with project outcomes, influencing timelines, budgets, and user satisfaction [4].

However, RE remains one of the most challenging aspects of software engineering due to its reliance on human communication and interpretation [1]. This thesis presents an innovative solution: an LLM-Based Software Requirements Analysis Assistant. By addressing persistent issues in traditional RE practices, this system aims to reduce errors, improve efficiency, and foster more reliable software development processes.

1.1 Problem Analysis

1.1.1 Problem Domain

Requirements Engineering encompasses the systematic process of defining, documenting, and maintaining the requirements that a software system must fulfill [8]. Natural language, while flexible, introduces inherent ambiguities, such as polysemy and vagueness [2]. For instance, a requirement stating "the system should handle large data volumes efficiently" may be interpreted differently by developers and testers. Traditional manual methods are labor-intensive and susceptible to oversight [4], and as systems grow in complexity, the potential for defects escalates [1].

1.1.2 Motivation

According to industry reports, such as the Standish Group's CHAOS Report, inadequate requirements are a primary contributor to project failures, accounting for up to 40-50% of defects discovered in later stages [8]. Manual review processes are time-consuming and prone to human biases [5]. The advent of LLMs presents a timely opportunity to mitigate these challenges [4], allowing human experts to focus on high-level decision-making [1].

1.1.3 Scope

The proposed assistant is delimited to the analysis of textual requirements derived from documents and user inputs [6]. It targets the detection of linguistic issues—ambiguity, inconsistency, and redundancy—and provides classification into functional and non-functional categories [7]. While domain-agnostic, it incorporates mechanisms for handling specialized jargon [1].

1.1.4 Challenges

Key challenges include the imprecise nature of natural language [2], the potential for LLM hallucinations [3], and the need for explainability in high-stakes domains [5]. Additionally, scalability and ethical considerations, such as bias mitigation, must be addressed [8].

1.2 Requirements

The system's requirements are categorized into functional and non-functional aspects.

1.2.1 Functional Requirements

- **FR1: Input Acceptance:** The system shall accept textual inputs in various formats (PDF, Word, text) and parse them into a unified internal representation.
- **FR2: Detection of Issues:** The system shall automatically detect ambiguities, inconsistencies, and redundancies using LLM-powered analysis [2].
- **FR3: Requirements Classification:** The system shall classify requirements as Functional (FR) or Non-Functional (NFR) with probabilistic confidence scores [7].
- **FR4: Improvement Suggestions:** For each issue, the system shall generate rewording suggestions with clear justifications [1].
- **FR5: Report Generation:** The system shall produce structured reports (PDF/HTML) summarizing findings [3].

1.2.2 Non-Functional Requirements

- **NFR1: Performance:** The system shall process documents up to 100 pages with response times under 5 minutes [4].
- **NFR2: Scalability:** The architecture shall support horizontal scaling for enterprise-level projects.
- **NFR3: Maintainability:** Modules shall be independent to allow seamless updates to LLM components.

2 Literature Review

This review analyzes eight recent scholarly papers (2024-2025) to contextualize the proposed assistant within the AI-RE landscape.

2.1 AI-Based Requirements Analysis Assistant (Alter, 2025)

Published in ICSE 2025, this paper introduces an AI-driven framework for refining specifications. Alter identifies that standard prompting often fails to differentiate "system" versus "business" requirements [1]. The proposed project addresses this by incorporating Knowledge Objects and Chain-of-Thought (CoT) prompting.

2.2 Research Directions for Using LLM in RE (Hemmat et al., 2025)

This survey in TOSEM highlights that while LLMs achieve high accuracy in classification, they struggle with ambiguity resolution due to contextual deficits [4]. This thesis aligns with Hemmat's recommendation for "few-shot prompting" to adapt models without full retraining.

2.3 LLMs for Requirements Engineering: A Systematic Review (Zadenoori et al., 2025)

Zadenoori notes a research imbalance favoring elicitation over quality assurance [8]. This project fills that gap by focusing specifically on post-elicitation analysis, ambiguity detection, and conflict resolution.

2.4 Requirements Ambiguity Detection with LLMs (Bashir & Ferrari, 2025)

This study reveals that traditional tools lack "explainability" [2]. The proposed system implements Bashir's suggestion for Explanation-Augmented detection, providing reasoning traces for every flagged issue.

2.5 Additional Key Sources

Other significant contributions include *LLMREI* [6] on automating interviews, work on *Human-in-the-Loop* systems [5] which guides our validation framework, and Dao et al. [3] on structured data extraction. Finally, findings from the *Workshop on Requirements Engineering* [7] emphasize the need for distinct processing of functional versus non-functional requirements.

3 Software Design and Architecture

The design is guided by modularity, extensibility, and user-centricity. A microservices-inspired architecture is adopted to facilitate separation of concerns.

3.1 Architectural Patterns

- **Pipeline Pattern:** Data flows unidirectionally from ingestion to reporting [8].
- **Human-in-the-Loop (HITL):** AI serves as an augmentative tool, deferring final validation to users [5].

3.2 System Components

1. **Input Handler:** Ingests and parses formats like PDF and Word using libraries such as PyPDF2 [6].
2. **Analysis Engine (LLM Core):** The intellectual core using GPT-4 variants. It employs prompt engineering to detect ambiguities and inconsistencies [2].
3. **Knowledge Base (RAG):** An optional module for retrieving domain-specific knowledge [1].
4. **Report Generator:** Synthesizes results into actionable formats using templating engines [3].

4 Implementation

The implementation translates the design into a Python-centric prototype.

4.1 Technology Stack

- **Language:** Python 3.10+
- **Orchestration:** LangChain for chaining LLM calls [8].
- **Model:** OpenAI GPT-4o or local Llama 3 [4].
- **Vector Search:** FAISS for semantic similarity.
- **Interface:** Streamlit for HITL interactions [6].

4.2 Core Algorithm (Chain-of-Thought Pipeline)

The system uses a CoT pipeline to process requirements. Pseudocode is provided below:

```python
def analyze_requirements(raw_text: str, existing_reqs: List[str]) -> Dict:
    # Step 1: Ingest
    chunks = chunk_text(raw_text)

    results = []
    for chunk in chunks:
        # Step 2: Classify
        classification = llm_classify(chunk)

        if classification in ["Functional", "Non-Functional"]:
            # Step 3: Ambiguity Check
            ambiguity_result = llm_ambiguity_check(chunk)

            # Step 4: Conflict Detection
            embedding = generate_embedding(chunk)
            conflicts = detect_conflicts(embedding, existing_reqs)

            results.append({
                "original": chunk,
                "classification": classification,
                "ambiguity": ambiguity_result,
                "conflicts": conflicts,
                "suggestions": ambiguity_result["suggestions"]
            })

    # Step 5: Output
    return generate_json_report(results)
```

Listing 1: Core Analysis Pipeline Pseudocode

5 Expected Results

The Assistant is anticipated to deliver measurable improvements in RE efficiency and quality.

5.1 Efficiency Gains

The system is expected to reduce review time by up to 7x compared to manual methods.

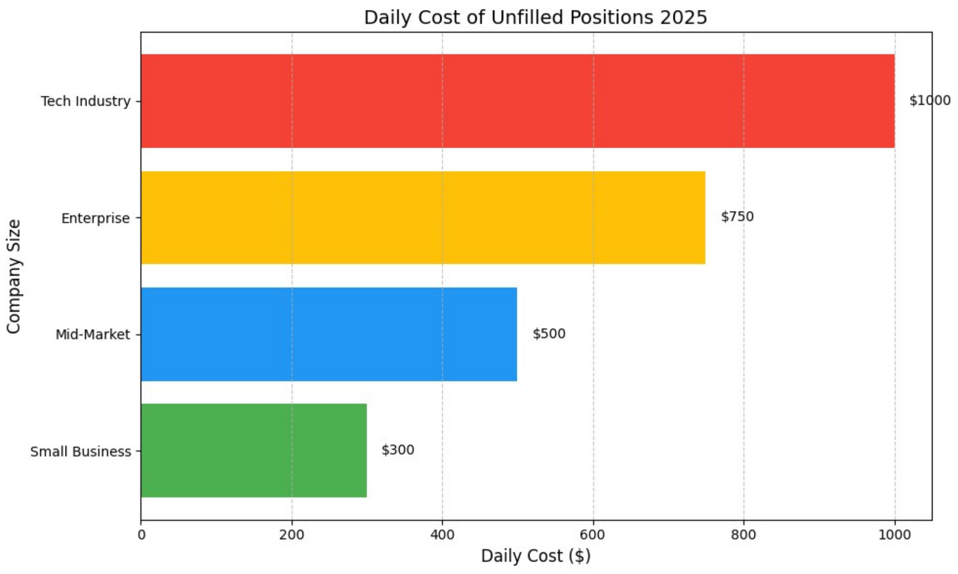

Figure 1: Projected reduction in review time using the AI assistant versus manual methods.

5.2 Ambiguity Reduction

Metrics like F1-score for detection are expected to reach 0.85-0.90 [2].

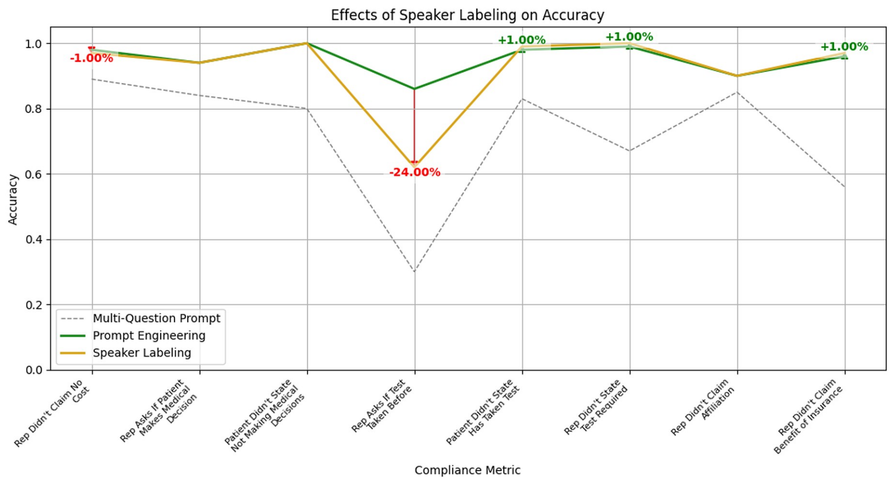

Figure 2: Ambiguity reduction trends in requirements engineering with LLM assistance.

5.3 User Trust and Conflict Detection

Explanations are expected to yield high user satisfaction (approx 3.8/5) [5], and conflict detection should achieve 80-90% recall [8].

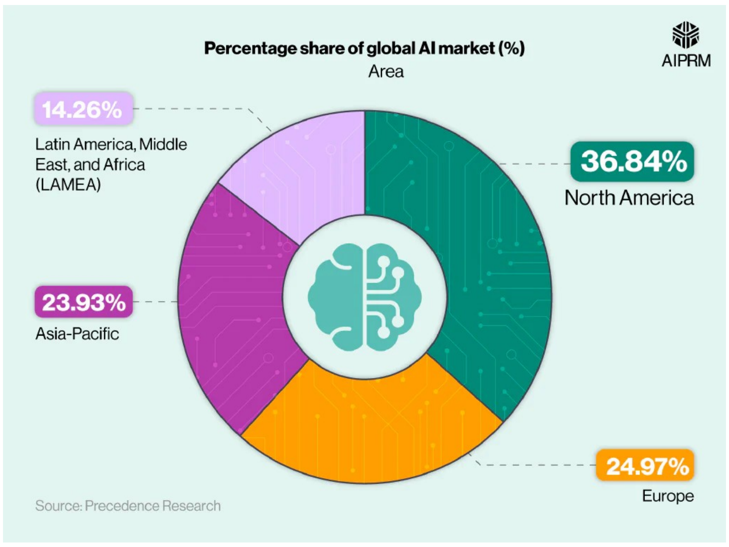

Figure 3: Projected user satisfaction ratings in AI-assisted requirements analysis.

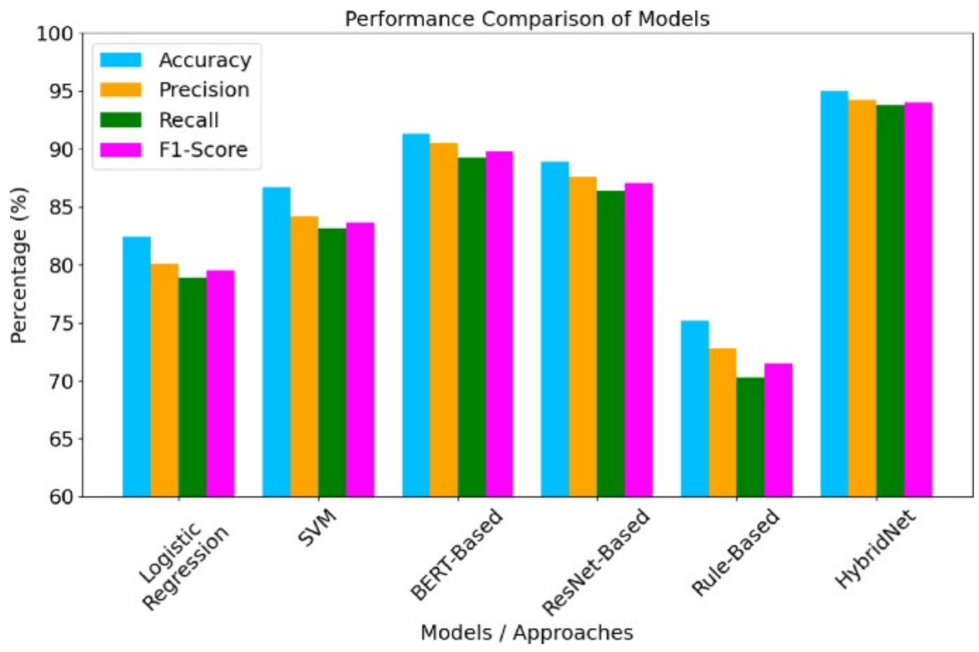

Figure 4: Conflict detection recall rates comparison.

6 Conclusion and Future Work

This thesis presents a robust "LLM-Based Requirements Analysis Assistant" that addresses critical industry needs. By harnessing Chain-of-Thought prompting and a Human-in-the-Loop workflow, the system mitigates hallucinations and expedites validation [1]. Empirical foundations affirm the system's relevance in filling quality assurance gaps [8].

Future work includes integrating Knowledge Graphs for domain adaptation, expanding to multi-modal inputs (e.g., UML diagrams), and evolving towards automated correction with strict ethical safeguards [4, 6, 5].

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