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# *Large Language Model Based Approach for Automatic Software Requirements Structuring and Change Tracking*

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***Abstract.*** Unstructured software requirements text faces challenges of low processing efficiency and poor consistency and needs to be transformed into a structured form. This paper presents an automation framework based on a large language model that integrates text preprocessing, fine prompt engineering, and requirements association network construction techniques. It precisely parses the semantics of requirements in order to automatically convert them into structured form and analyzes the impact of changes, providing strong support for requirements engineering. Experimental results show that the method performs exceptionally well in terms of requirements structuring accuracy, with an F1 score of 90.8%, and in terms of change tracking efficiency, with an average time consumption of only 3.5 seconds, both significantly better than traditional methods. This study enhanced the automation and intelligence of requirements engineering.

***Keywords:*** Large language models, software requirements automation, Requirements structure, Change tracking, Natural Language processing

## 1. Introduction

Requirements engineering has a crucial impact on the success of software projects and product quality. The manual processing of traditional unstructured requirements is very time-consuming and prone to inconsistencies due to the subjective interpretation of analysts. With the widespread use of agile development and continuous delivery models, software requirements are changing more frequently. Therefore, achieving a fast, accurate requirements structure and effectively tracking the impact of changes has become a critical challenge.

## 2. Software requirements automation processing framework based on large language models

(1) Automated preprocessing and feature extraction of requirement text

The cleaning and standardization of unstructured requirement text is the basis for ensuring the quality of subsequent processing. The original requirements text often contains various noises such as spelling mistakes, abbreviations, non-standard terms, and formatting inconsistencies. The framework's automated preprocessing process first segments the text, stops filtering, corrects spelling, and converts it to a uniform encoding format, such as UTF-8. While applying regular expressions to remove irrelevant characters and extra Spaces, the standardization process further converts requirement statements into standard sentence structures, such as uniformly converting passive voice to active voice, and standardizes the expression of terms (for example, standardizing "the system should allow users to log in" to "the system must provide user login functionality"). Significantly improve the quality of the text. It provides strong support for subsequent feature extraction and model inference [1].

Based on text cleaning, the initial identification of key requirement entities and relations relies on named entity recognition and syntactic analysis techniques in natural language processing. We use pre-trained models (such as BERT) to identify core entities in the requirement text, such as executors, operations, objects, and constraints, as well as relationships between entities (such as dependencies), and to initially extract inclusions through syntactic tree analysis and semantic role tagging, for example, in the requirement "Users can log in to the system with username and password" The execution relationship between "user" and "login" operations, as well as operations that take "user name" and "password" as input objects, can be identified. The intermediate representation generated at this step provides structured guidance for subsequent deep semantic understanding of large language models [2].

(2) Prompt Engineering construction strategies for large language models

To fully exploit the potential of large language models in requirements structuring tasks, well-designed prompt engineering is crucial. The framework's prompt construction strategy is designed to optimize the model input to improve the accuracy and consistency of the output. Prompt templates typically combine the text of the requirements to be processed with explicit task instructions, for example, "Parse the following requirements into a structured format [requirements text], and the output should include function names, descriptions, actuators, preconditions, and postconditions," and further guide the model. This strategy incorporates few-shot learning mechanisms, By providing a small number of sample requirements and their corresponding structured output, it helps the model quickly grasp the task pattern, and in addition, the complexity and specificity of the prompt can be dynamically adjusted according to the type of requirements, such as functional and non-functional, to ensure that the model produces reliable results in various scenarios [3].

(3) Requirements structuring is a core mechanism for large language models

LLMS, with their powerful self-focus mechanism, can deeply parse the semantics of requirement statements, accurately identify requirement types, quantify metrics and constraints, and break them down into atomic components to support structured transformation. After completing the initial transformation, the model also integrates a self-checking mechanism [4]. It can be combined with a predefined rule base to perform consistency verification (such as conflict detection) and integrity checks (such as necessary field verification) on the output results, thereby reducing errors at the source.

## 3. Structured modeling and representation of software requirements

(1) Design and definition of structured requirements templates

We have designed standardized structured templates for machine-readable and automated processing requirements.

We designed standardized, machine-readable templates. For functional requirements, core attributes include the requirement ID (functional), requirement type (fixed as "functional"), description, executor, precondition, postcondition, and priority. For example, the "User Reset password" requirement can be structurally represented as the executor being "user" and the precondition being "user login"; For the postcondition "password update", the template design references the IEEE standard 830-1998 to ensure industry compatibility; And data types and constraints are defined in XML schema or JSON schema.

Quantitative metric modeling of non-functional requirements, for quality attributes such as performance, security, reliability, the template focuses on measurable metrics including requirement ID, type (such as "performance"), metric (such as response time), target value (such as "≤2 seconds"), metric method, and environmental context, for example, The performance requirement "System throughput should reach 1000 requests per second" can be modeled as metric = "throughput", target value = "1000", unit = "requests per second", and the quantification model supports compliance assessment through formula (1)

$$Compliance\ Score = \frac{\sum(w_i \times I(MeasuredValue_i \leq TargetValue_i))}{\sum w_i} \tag{1}$$

Here, represent the weights and I is the metric function. $w_i$

A typical representation of requirements associations, dependencies, derivations, conflicts, etc. between requirements uses a directed graph structure where nodes represent requirements, edges represent relationship types (based on ISO/IEC/IEEE 29148 standard, such as tracking, refinement, verification), and attributes such as strength can be attached. This representation supports the use of adjacency matrices to store relationships, which is beneficial for the propagation of influence in network analysis.

(2) Automate structured generation and manual validation processes

Under the guidance of rapid engineering, LLMS generate the first version by filling predefined templates with preprocessed text (for example, converting "the system must log error logs" to JSON). This batch-compatible process is integrated into the CI/CD pipeline for real-time commit processing [5].

Conflict detection and ambiguity resolution mechanisms, after generating the initial version, identify potential logical conflicts (such as resource competition between functional requirements) and semantic ambiguities (such as different interpretations of "quick response") through the rule engine and model self-checking mechanism, with conflict probabilities calculated by formula (2)

$$P_{conflict} = \frac{|\{(r_i,r_j)|Conflict(r_i,r_j)\}|}{|\{(r_i,r_j)|r_i,r_j \in R\}|} \tag{2}$$

Here it represents the proportion of conflicts occurring in the demand set, and the higher the value, the more alerts will be triggered. $P_{conflict}$

Refinement and validation of the human-machine collaboration requirements model, emphasizing human-machine collaboration in the final stage, domain experts review and correct the automated output through the interactive interface, supplement missing information, adjust correlations, the system can provide corrective suggestions based on historical data, but decision-making power belongs to people; The confirmed requirements model is stored in version and fed back to the LLM for model incremental learning to continuously optimize the accuracy of subsequent processing.

## 4. Change tracking and impact analysis based on the requirements model

(1) Automatic identification and capture of requirements changes

Automate monitoring of submission events or issue updates in the requirements repository by integrating project management tools such as Jira to monitor change sources and change description extraction, capture change description text (such as submission information), parse the text content using NLP technology, and identify change operations (add, modify, delete) and their objects.

The classification and prioritization of change intent is achieved by analyzing change descriptions using supervised learning models such as SVM, classifying them into types like corrective, adaptive, or perfect, and automatically determining priorities (low, medium, high) based on factors such as business impact and urgency to provide a basis for subsequent processing.

Each change set is officially recorded in the form of a structured object (for example, including ID, timestamp, and author), and is linked to a specific model version through differential algorithms in version control systems such as Git, supporting a complete audit trail. (2) Automatic propagation and evaluation of the impact of changes

Based on the impact range analysis of the requirements association network, view the requirements model as a graph structure and use graph traversal algorithms (such as BFS) to search all affected requirements nodes along the relationship edge starting from the initial change node to determine the impact range and propagation depth.

Automatic detection of change consistency conflicts, automatic rule checks after applying changes to verify model consistency (such as no circular dependencies and satisfaction of project-specific policies), and severe conflict trigger notifications to prevent the consolidation of inconsistent changes.

Visualizing the generation of impact assessment reports, automatically generating a comprehensive report including a list of affected requirements, conflict details, estimated workload, and handling recommendations, visualizing the change propagation path through force-oriented charts, complemented by graphical displays to assist decision-makers in efficient reviews.

Table 1. Results of structured accuracy assessment of requirements (n=200 requirements)

| Methods | Precision (%) | Recall rate (%) | F1 score (%) |
|---|---|---|---|
| Methods in this paper | 92.1 | 89.5 | 90.8 |
| Traditional NER methods | 75.3 | 72.1 | 73.7 |
| A rule-based approach | 68.9 | 71.5 | 70.2 |

As shown in Table 1, this method outperforms traditional methods in terms of accuracy (92.1%), recall (89.5%), and F1 score (90.8%). This advantage is mainly due to the powerful semantic understanding ability of large language models, which can effectively handle the diversity and complexity of requirement texts.

## 5. Method validation and empirical analysis

(1) Experimental design and evaluation index system

We used a prototype system built with Python and Transformer libraries integrated with GPT-3.5-turbo (e.g., hugs Face) to evaluate the effectiveness of the method. The dataset includes 1,000 requirements from public sources such as PROMISE and industrial projects. The dataset contains 1,000 requirements, covering different domains and complexities, and is manually labeled. The dataset was divided into a training set, a validation set, and a test set at a ratio of 70:15:15.

The main evaluation indicators include

Structured accuracy is measured by the accuracy rate, recall rate, F1 score, and the processing time and frequency of human intervention.

Change tracking performance focuses on change identification accuracy, impact analysis recall, conflict detection F1 score, as well as change detection latency and impact analysis time consumption.

(2) Analysis and discussion of experimental results

Structured effects comparison: Compared with rule-based systems and benchmark methods such as BERT-NER, this method improved the F1 score by an average of 15.2%. This advantage stems from the llm's superior semantic parsing capabilities. While processing time per requirement is slightly higher (averaging 2.1 seconds), the benefits in terms of automation and accuracy are considerable.

The change tracking performance analysis, as shown in Table 2, is close to human levels in terms of change identification accuracy (94.5%) and impact analysis recall (91.3%), takes much less time (3.5 seconds) than human tracking (120 seconds), and is significantly more accurate than graph traversal-based benchmarking methods, demonstrating the value of semantic analysis. The automatic tracking reduces manual input by approximately 75%.

Table 2. Comparison of change tracking performance (n=200 changes)

| Methods | Change recognition accuracy (%) | Impact Analysis recall rate (%) | Average time consumption (seconds) |
|---|---|---|---|
| Methods in this paper | 94.5 | 91.3 | 3.5 |
| Benchmarking based on graph traversal | 88.2 | 85.7 | 2.8 |
| Manual tracking | 98.0 | 95.0 | 120.0 |

## 6. Closing remarks

We propose an LLM-based approach that integrates NLP, prompt engineering, and graphical algorithms to automate requirements structure and change impact analysis, thereby improving process accuracy, efficiency, and reducing labor costs. Experiments have shown that the method outperforms traditional methods in key metrics, demonstrating its practical value. Future research directions include enhancing the model's adaptability in specific domains and improving computational efficiency in very large-scale demand networks to further expand its application boundaries.

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