

Original Article

How Natural Language Processing Framework Automate Business Requirement Elicitation

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Abstract - Requirement elicitation is an important and critical phase in the software development lifecycle, but it is exposed to inefficiencies and human error as it is dependent on manual methods such as interviews, workshops, and document analysis [1-4]. With the growing complexity of modern systems and the increasing volume of unstructured data, there is a need for innovative solutions to address these challenges. This paper explores the use of Natural Language Processing (NLP) to automate some important aspects of the requirement elicitation process by using advanced NLP techniques, such as the Named Entity Recognition (NER) framework, which aims to extract relevant business requirements from various unstructured sources, including emails, transcripts, and documents. This automation improves the accuracy and traceability of the elicited requirements by reducing the manual effort required. This paper, by taking an example of a banking use case, demonstrates how this framework helped in not only reducing the time spent on the requirement elicitation significantly but also discovering a lot of undocumented yet important requirements. This paper also highlights the challenges and importance of human oversight with this framework in regulated industries. Finally, the paper concludes by providing future direction/guidance, including how AI systems can be integrated into the core ecosystem and help with interactive requirement elicitation.

Keywords - Artificial intelligence, Automation, Natural language processing, Business analysis, Requirement elicitation.

1. Introduction

Requirement elicitation serves as the blueprint, especially in large-scale digital transformation projects. In the traditional world, human-driven techniques such as interviews, workshops, and document analysis are used. Although these methods are time-consuming, they are also prone to error due to human subjectivity, ambiguity in communication, and inconsistent documentation. This primarily is the basis of the problem statement addressed in this paper.

In today's world, organizations use vast amounts of unstructured data—including emails, transcripts, support tickets, and legacy documents - and there is a strong need for intelligent automation. Natural Language Processing (NLP) offers powerful capabilities to understand, summarize, and extract business intent from textual data [5].

This paper explores the use of NLP to transform business requirement elicitation from a manual effort into an intelligent, semi-automated process. This includes:

- A modular NLP-based architecture for requirement extraction
- A banking industry use case demonstrating practical

implementation

- Evaluation of risks, ethical considerations, and future enhancements

This paper addresses the research gap between various available papers on requirement elicitation and those on NLP and AI, bringing them together to automate tasks and thereby reduce manual errors.

2. Literature Review

Requirement engineering has always been a critical aspect irrespective of being in any SDLC cycle: waterfall or agile. Over the last few years, there has been considerable interest and a surge in papers on requirement engineering and elicitation. Various papers listed in the references focus on the contributions of various contributors to the project's success and emphasize the critical role of requirements engineering in these factors, as well as the issues and challenges faced during requirements elicitation. Some of the details can be found in the papers written by H. F. Hofmann and F. Lehner, Tabbassum I. & Mouhammad S., and Q. A. Shreda and A. A. Hanani.

There are other papers that can be found that have research on NLP and Machine Language Approaches for



functional and non-functional requirements, written by Nazir, F., Butt, W.H., Anwar, M.W., Khan Khattak, and P. Mishra, K. Ninawe, K. Dhawle, S. Prasad, A. Band, and P. Dubey.

This paper has tried to bring both the above-mentioned aspects together and showcase how NLP helps in requirement elicitation and how it can remediate the challenges and issues seen with the manual process of elicitation.

3. Research Gap

Existing research papers focus on NLP and its use cases; while there are other use cases on how to automate business analysts' tasks, this paper attempts to bring NLP and business analysts' tasks/use cases together, hence bridging the gap between these research done so far.

4. Background and Problem Statement

Manual steps in the current practices for requirement elicitation led to a lot of inefficiencies, inconsistencies, and unstructured data, which is the primary problem statement that is addressed in this paper.

Though there could be a lot of reasons for project delays, requirement elicitation is one of the common root causes. Studies show that over 40% of defects in enterprise software projects are due to misunderstanding or incomplete requirements. The process is challenged by

- The volume of unstructured text
- Ambiguity in stakeholder language
- Knowledge silos across teams
- Lack of traceability and change impact analysis

NLP provides a way to structure this chaotic data by identifying entities, relationships, topics, and sentiments [3]. By integrating NLP into the requirement engineering

lifecycle, businesses can reduce manual effort and surface hidden or implied requirements early in the project lifecycle.

5. NLP Techniques for Requirement Elicitation

The core NLP techniques leveraged include [2]:

- Named Entity Recognition (NER): Identifies domain-specific entities like systems, customers, regulations, or monetary amounts. Useful for identifying scope boundaries.
- Dependency Parsing: Analyses grammatical structure to extract relationships from sentences.
- Topic Modelling: Applies algorithms like LDA to cluster similar themes such as authentication, compliance, etc.
- Sentiment and Intent Detection: Identifies urgency or detects sentiments in stakeholder conversations.
- Text Summarization: Extracts key points from long documents into concise requirement statements.

6. Proposed Architecture

The architecture is designed to process unstructured data and convert it to structured and actionable business requirements.

It has the following high-level layers:

- Input Layer – Serves as the interface with various sources for the data
- Preprocessing Layer – It cleans the raw data from the Input Layer for NLP analysis.
- NLP Engine – it does various processing to provide business requirements. This includes but is not limited to, named entity recognition, requirement classification, requirement creation, and traceability.

Below is the proposed modular NLP architecture:



Fig. 1 High-Level NLP-Driven Elicitation Workflow

7. Use Cases

7.1. Use Case for Illustrative Purposes

In a large-scale core banking replacement program, over 400 hours of stakeholder discussions and 300+ policy documents were fed into the proposed system.

7.1.1. Observed Outcomes

- Time Saved: 45% reduction in manual documentation effort.
- Requirement Coverage: 18 previously undocumented compliance items were discovered.
- Traceability: Each requirement was auto-linked to its source (document or speaker).

7.1.2. Sample Extracted Requirement

From the statement: “All transactions over \$10,000 must be flagged for compliance review.”

7.1.3. NLP Extract

- Entity: Transaction
- Rule: Threshold = \$10,000
- Action: Flag for compliance
- Result: Mapped to a functional requirement.

7.2. Actual Use Cases from Industry

7.2.1. Use Case 1

IBM used Watson NLP to process regulatory documents, extract compliance requirements, and map them to IT system rules.

Outcome: Accelerated requirement analysis for insurance product updates.

Reference: IBM Watson whitepapers and case studies (e.g., “Watson Discovery for Regulatory Compliance”) [8].

7.2.2. Use Case 2

Accenture developed internal NLP tools to mine user stories and extract acceptance criteria from email threads and ticketing systems like Jira.

Outcome: Reduced time spent by business analysts by ~30%.

Reference: Accenture Labs publications (not always publicly detailed but cited in trade literature) [9].

7.2.3. Use Case 3

Capgemini applied NLP to analyze policy documents

and meeting transcripts for government digital transformation.

Goal: Automate initial draft requirements for citizen-facing platforms [7].

Outcome: Improved first-pass accuracy and policy traceability.

8. Challenges and Limitations

Below are some of the challenges:

- Ambiguity and Vagueness: Stakeholder language is often implicit, and NLP models struggle without domain context.
- Domain Language: Banking-specific terms require custom-trained models to achieve high accuracy.
- Human Oversight: Human validation remains essential for finalizing requirements, especially in regulated sectors.
- Data Privacy: NLP systems must comply with data protection laws such as GDPR and CCPA.

9. Future Directions

With the rise of large language models (LLMs) like GPT, there is potential for deeper understanding and automation [5]:

- Chat-based interactive requirement elicitation
- Context-based risk prediction
- Auto generation of user stories and test cases

Integration with tools like Jira or Azure DevOps will allow seamless ingestion and traceability of requirements.

10. Conclusion

NLP presents a transformative opportunity for automating business requirement elicitation. By integrating structured linguistic analysis with domain expertise, organizations can improve efficiency, enhance coverage, and reduce misinterpretation. While full automation is not yet advisable, a human-in-the-loop model offers a practical middle ground for immediate gains.

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