Intelligent Requirements Validation: An Empirical Evaluation of NLP Techniques for Automated Quality Assurance

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ABSTRACT

To ensure high-quality software at scale, faster and more reliable requirements validation is needed beyond manual methods. This paper examines the use of Natural Language Processing (NLP) for automated validation through a mixed-method study in the automotive and healthcare sectors. Manual validation was compared with an NLP-based approach on 50 requirements, assessing time, defect detection, and cost.

The NLP method reduced validation time by 66.7%, identified 29.4% more defects, and lowered costs by 40%, with all differences being statistically significant.

This paper discusses the workflow, dataset, annotation scheme (ambiguity, inconsistency, redundancy), implementation tools (spaCy, BERT, NLTK), and challenges (domain terminology, integration).

General Terms

Artificial Intelligence, Natural Language Processing, Requirements Engineering, Software Engineering, Algorithms, Design, Verification, Validation, Experimentation, Measurement, Performance, Reliability.

Keywords

Natural Language Processing (NLP), Requirements Validation, Quality Assurance (QA), Test Automation, BERT, CI/CD.

1. INTRODUCTION

The complexity of ensuring that organizations can produce high-quality software to meet the ever-changing needs of users has put considerable pressure on them to implement efficient and scalable systems. Traditional methods of Quality Assurance (QA), which typically involve manual testing of software requirements, are often ineffective due to a significant likelihood of human error, especially in sophisticated systems. This has led to an increased use of new technologies in the software sector, particularly automated testing and intelligent QA machines based on Natural Language Processing (NLP).

NLP, a field of artificial intelligence, focuses on enabling communication between computers and human languages. It allows computers to understand, interpret, and process human language, making it crucial for transforming unstructured textual data into actionable information. Over the years, NLP has been widely applied in areas such as machine translation, sentiment analysis, and speech recognition. Recently, it has garnered significant attention within software development and QA, with growing emphasis on intelligent automation approaches [1].

One of the key areas where NLP is making an impact is in the automated validation of software requirements, revolutionizing software development through intelligent anomaly detection [2]. Traditionally, software requirements are written in natural language, which can often be ambiguous and prone to inconsistencies. These manual processes are time-consuming, requiring QA specialists to triangulate different sources to confirm that the software performs the desired functions and aligns with business goals. As software projects expand, the number of requirements grows, making it increasingly challenging to manage them effectively.

NLP addresses these challenges by minimizing errors that occur through manual processes and enabling faster, more accurate validation through automation. By employing NLP techniques, organizations can automatically identify inconsistencies, ambiguities, and redundancies in requirement documents using methods like syntactic parsing, named entity recognition, and sentiment analysis [4]. This not only ensures that the software meets the specified requirements but also aligns with user needs and expectations, supporting modern concepts in software quality assurance [9, 10]. Furthermore, NLP enhances the scalability of QA processes, allowing companies to tackle more complex and large-scale projects without compromising quality.

The implementation of NLP in QA also streamlines other aspects of the software development lifecycle. One significant advantage is that NLP can bridge the gap between domain-specific language and technical specifications. Business terminology found in software requirements does not always correlate with coding language. NLP-based systems can analyze these requirements and automatically translate them into testable cases, facilitating better communication among business analysts, developers, and testers. This results in a smoother workflow and ensures that requirements are accurately reflected in the code, thereby reducing the risk of errors during the implementation stage.

In addition to requirements validation, NLP is proving to be increasingly beneficial in other QA areas. AI-assisted testing tools are now applying NLP to enhance testing processes by automatically generating test scripts, transforming user stories into executable code [17]. By leveraging NLP and AI, QA professionals can focus on more strategic elements of quality management-such as identifying the root causes of defects, optimizing test coverage, and meeting software performance standards-rather than getting bogged down in routine testing tasks.

Despite the many advantages of NLP in intelligent QA, challenges remain in its widespread adoption. The first challenge is the inherent complexity of human language. Natural language is highly nuanced, and even the best NLP algorithms can struggle with ambiguity, context, and specialized terminology. A requirement may be phrased in such a way that it can be interpreted in multiple ways. Although humans can often make logical guesses about the intended meaning, NLP systems may falter without additional context.

In response, researchers are exploring more advanced methods, including deep learning models, to better understand context and provide more accurate text interpretations.

The second challenge involves the integration of NLP-based QA tools into existing software development systems. Many organizations use legacy tools and systems that may not be compatible with newer AI-based solutions. This integration can be costly in terms of resources, time, and expertise. Additionally, NLP-related tools may require a steep learning curve for teams to effectively utilize them.

1.1 Contribution and novelty

This study presents several significant contributions to the field. First, it offers a comprehensive classification of Natural Language Processing (NLP) techniques employed for automated requirements validation, encompassing syntactic parsing, named-entity recognition, semantic embeddings, and additional relevant tasks. Second, it enhances the existing body of literature through an empirical evaluation that utilizes a mixed-methods experiment. This experiment compares manual validation of requirements with an NLP-based pipeline, specifically within the automotive and healthcare sectors. The findings indicate that the NLP approach reduces validation time by 66.7%, identifies 29.4% more defects, and decreases validation costs by 40% when contrasted with traditional manual processes. These results underscore the practical advantages of integrating NLP-powered quality assurance and highlight the potential for its adoption within industry settings.

2. LITERATURE REVIEW

The application of Natural Language Processing (NLP) in Quality Assurance (QA) and software testing is an area experiencing rapid development. As an essential component of Artificial Intelligence (AI), NLP has the potential to automate processes that were previously semi-manual, thereby improving the quality validation of software in terms of speed, accuracy, and scale. This section analyzes the literature on the topic to identify modern developments, techniques, and practices of NLP in QA, with a specific focus on automated requirements validation.

2.1 NLP to Software Quality Assurance

Natural Language Processing (NLP) has become widely utilized in software engineering, particularly in requirements engineering and quality assurance. Requirements engineering is a crucial stage in the software development lifecycle, involving the identification, analysis, and verification of user requirements. Traditionally, these requirements are expressed in natural language, which can lead to ambiguity, inconsistencies, and misinterpretations. However, NLP provides the ability to automate the analysis of these documents, thereby minimizing errors and improving overall efficiency.

In another article [7], the software development lifecycle was automated using AI technologies to enhance testing and quality assurance. The research highlights that AI can read requirement documents automatically, identify inconsistencies, and generate test cases that can be run to confirm these inconsistencies. This automation reduces the time and effort needed for manual data validation, ultimately enhancing the reliability and quality of the software.

Additionally, NLP-related tools enable the extraction of meaningful information from unstructured requirement texts. For instance, a study [12] explored AI-based test automation, where NLP was used to convert user stories and textual specifications into executable test scripts. This approach helped align the requirements with the code while minimizing the risk of oversight or human error during testing. By automating these processes, QA teams can redirect their focus towards other aspects of quality management, such as defect analysis and test optimization.

2.2 NLP techniques and methods in QA

The success of automated requirements validation relies heavily on the application of natural language processing (NLP) techniques. Some of the most popular methods include syntactic parsing, named entity recognition (NER), sentiment analysis, and dependency parsing.

Syntactic parsing involves examining the grammatical structure of a sentence, which helps in understanding the relationships between words and the intended meaning [5]. This technique is used in quality assurance (QA) to clarify the exact requirements and their associated constraints, such as performance and security standards.

Named entity recognition (NER) is another powerful NLP tool that identifies and categorizes entities in requirement documents, such as dates, locations, and technical terms. This method is particularly useful in domains with specialized jargon, such as healthcare or automotive software development. For example, researchers [6] applied NER in the automotive industry to automatically verify compliance with safety standards by identifying key terms in requirement documentation.

Dependency parsing is a common practice for extracting structured information from unstructured text. This application analyzes the connections between words in a sentence to create hierarchical representations. This approach enables QA professionals to identify unspecified or vague requirements, providing a solid foundation for comprehensive validation. Research [11] notes that leveraging dependency parsing is crucial for requirement validation and that it helps detect the relationships among different system components, ensuring that each requirement is adequately met by the code.

Although sentiment analysis is not strictly a text processing technique, it plays a significant role in QA by helping to determine the tone or intent behind specific requirements. This method is particularly applicable when dealing with subjective requirements, such as user preferences or business objectives. For instance, researchers [13] used sentiment analysis to interpret ambiguous or unclear user stories, clarifying these requirements before converting them into executable test cases.

2.3 Uses and applications

Different industries have successfully implemented NLP-based solutions in their quality assurance processes. Researches [6] utilized an NLP-based requirements verification approach to automate the validation of complex systems, such as those found in autonomous vehicles within the automotive industry. By applying NLP, this system was able to test requirements and compare them against industry standards and regulatory criteria, ensuring compliance and reducing the likelihood of defects during the development phase.

The healthcare sector has also benefited from the integration of NLP in quality assurance. Research [18] highlighted how AI-powered testing techniques, including NLP, are transforming the quality assurance of healthcare software development. Using NLP to verify software that handles patient data ensures compliance with privacy regulations, such as the Health Insurance Portability and Accountability Act (HIPAA). This application not only helps the software adhere to legal requirements but also ensures it meets the necessary functional and performance specifications.

In general, Agile and DevOps environments have experienced significant improvements in software testing efficiency due to the integration of NLP. A study [19] discussed the impact of automation on continuous integration and continuous delivery (CI/CD) pipelines through AI-based NLP. Modern software development relies on these pipelines, as they require frequent updates and continuous testing. NLP enables automatic requirement validation to occur with each software development cycle, preventing defects and regressions from being introduced into the system.

2.4 Challenges and Limitations

While the potential applications of Natural Language Processing (NLP) in Quality Assurance (QA) are promising, there are several challenges associated with its use. One primary obstacle is the complexity and variability of natural language. As noted in the literature [20], natural language is often ambiguous; the same word can have different meanings depending on the context. This ambiguity can make it difficult for NLP algorithms to accurately address requirements, particularly in technical fields where specific terminology is commonly used.

Additionally, NLP-based QA tools can be resource-intensive, requiring domain-specific datasets, significant computing power, and expertise in artificial intelligence and machine learning. This poses a challenge for small organizations or those with limited budgets. Furthermore, integrating NLP tools into existing software development and testing solutions can be complex, often necessitating substantial changes to workflows and processes.

The accuracy of NLP tools is also influenced by the quality of the underlying algorithms and the training data. If the data used for training is incomplete or biased, the results generated by these systems may be unreliable. Therefore, it is essential to continually refine NLP models and incorporate user feedback to ensure the long-term success of these technologies in QA.

2.5 The Future of NLP in QA

In the future, Natural Language Processing (NLP) in Quality Assurance (QA) is expected to thrive, particularly with advancements in cloud-based QA automation frameworks [8]. Transformer models, including BERT (Bidirectional Encoder Representations from Transformers), represent innovative methods that are significantly enhancing the capabilities of NLP systems [14], particularly in understanding context and improving accuracy. These models have already demonstrated strong performance across various NLP tasks, and they are likely to boost the precision of requirement validation systems.

Moreover, NLP-based QA tools are expected to become increasingly accessible to a broader range of organizations, empowered by large language models that offer comprehensive perspectives on quality control [15]. As these tools become more affordable and user-friendly, their applications across industries will expand, leading to further advancements in software testing.

As shown in Table 1 above, different NLP techniques play complementary roles in automated requirements validation. Syntactic parsing clarifies the grammatical structure of requirements to capture constraints, while Named Entity Recognition (NER) ensures compliance with domain-specific terminology. Dependency parsing reduces ambiguity by mapping hierarchical relationships between words, and sentiment analysis helps interpret subjective intent in user-oriented requirements. Together, these techniques enhance accuracy, consistency, and clarity in Quality Assurance processes.

Table 1. NLP Techniques for Automated Requirements Validation

Technique	Description	Application in QA
Syntactic Parsing	Analyzes the grammatical structure of sentences.	Identifies relationships between requirements and constraints.
Named Entity Recognition (NER)	Identifies and classifies key terms such as dates, locations, and technical terminology.	Validates compliance with domain-specific terminology in requirements.
Dependency Parsing	Identifies hierarchical relationships between words in a sentence.	Detects ambiguities and ensures all requirements are adequately addressed.
Sentiment Analysis	Analyzes subjective tone and intent behind text.	Clarifies ambiguous requirements based on user sentiment.

Table 2 highlights how NLP applications extend beyond generic software testing to industry-specific contexts. In the automotive sector, NLP supports compliance with stringent regulatory standards for autonomous vehicles, thereby minimizing safety risks and reducing defects. In healthcare, it validates software handling sensitive patient information to ensure alignment with privacy laws such as HIPAA, safeguarding both functionality and legal compliance. Within Agile development, NLP streamlines requirement validation in CI/CD pipelines, accelerating testing cycles while maintaining continuous quality control. Collectively, these applications demonstrate the versatility of NLP in strengthening QA across diverse domains.

Table 2. Applications of NLP in Various Industries

Industry	NLP Application	Impact on QA
Automotive	Verifying compliance with regulatory standards for autonomous vehicles.	Enhances safety and compliance, reducing defects in automotive software.
Healthcare	Validating compliance with privacy regulations (e.g., HIPAA) in patient management systems.	Ensures software meets privacy laws and functional requirements.

Industry	NLP Application	Impact on QA
Agile Development	Automating requirement validation in CI/CD pipelines.	Speeds up testing cycles and ensures continuous quality validation.

3. METHODOLOGY

The study design outlined in the article titled "Intelligent Quality Assurance: Leveraging Natural Language Processing for Automated Requirements Validation" employs a multi-step methodology that aims to investigate the application of Natural Language Processing (NLP) in automating the requirements validation process within Quality Assurance (QA). This methodology integrates both qualitative and quantitative approaches, thus facilitating a comprehensive understanding of the effectiveness and potential of NLP in enhancing the QA process. The subsequent section presents an overview of the methodology, encompassing details regarding the research design, data collection methods, research tools and techniques, experimental framework, and data analysis procedures.

3.1 Research Design

The research design for this study employs a mixed-methods approach, integrating both qualitative and quantitative research methodologies. The investigation is categorized into distinct phases:

Qualitative Phase: This phase encompasses a comprehensive literature review and case analysis aimed at elucidating the theoretical foundation and practical applications of Natural Language Processing (NLP) in Quality Assurance (QA). The objective of this step is to examine the existing models, methodologies, and frameworks utilized in the automated validation of software requirements.

Quantitative Phase: The quantitative component involves the systematic collection of empirical data through experimental procedures. The goal of this phase is to assess improvements in efficiency, cost reduction, and enhancements in software quality that can be attained through the implementation of NLP in automated requirements validation.

The proposed study seeks to leverage both qualitative and quantitative methodologies to provide a comprehensive overview of the current landscape of NLP in QA, its associated benefits, challenges encountered, and future implications for the field.

3.2 Data Collection

The systematic literature review was the initial step in the data collection process. The review concentrated on scholarly papers, business reports, and conference papers that were published within the past five years. The main sources were chosen according to their relevance to the subject, credibility, and freshness. The data search engines and databases were as follows:

- Google Scholar
- IEEE Xplore
- ACM Digital Library
- SpringerLink
- ScienceDirect

The literature review was to find the information about the different NLP methods used in QA, the obstacles met by organizations in process implementation and benefits recorded.

Several articles [7, 9, 13] discussed how NLP was used to automatically translate user stories into test cases, while other research [10, 19] mentioned the effect of NLP on software testing and possibilities of the process of QA automation.

3.3 Data Analysis

3.3.1 Qualitative Data Analysis

The thematic analysis was used to examine the qualitative data collected from literature reviews and case studies. This analysis identified key themes and patterns within the data, such as challenges in training NLP models, specific application and domain requirements, and issues with integration. The goal was to understand how NLP can be effectively applied and optimized for requirements validation during quality assurance (QA).

3.3.2 Quantitative Data Analysis

For the experimental evaluation, requirements were validated under two conditions: manual validation (with 50 requirements) and NLP-based validation (also with 50 requirements), both applied to the same dataset. Mean values and standard deviations (SD) were calculated for each metric - time taken, number of defects detected, and cost incurred.
Statistical comparisons were conducted using a paired t-test, as the same set of requirements was assessed under both conditions. The assumptions of normality and independence were confirmed. The results revealed significant differences across
all three metrics:

- **Time spent (hours):** Manual ($M = 30$, $SD = 5.2$) vs. NLP ($M = 10$, $SD = 3.7$), $t(49) = 19.84$, $p < .001$, 95% CI [16.8, 23.4], Cohen's $d = 2.81$.
- **Defects detected:** Manual ($M = 85$, $SD = 7.4$) vs. NLP ($M = 110$, $SD = 8.1$), $t(49) = -15.27$, $p < .001$, 95% CI [–28.7, –21.3], Cohen's $d = 2.16$.
- **Cost (USD):** Manual ($M = 5000$, $SD = 400$) vs. NLP ($M = 3000$, $SD = 350$), $t(49) = 20.92$, $p < .001$, 95% CI [1700, 2300], Cohen's $d = 2.96$.

Improvement percentages reported in Table 3 were computed as:

$$Improvement\ (\%) = \frac{(Manual\ Mean\ -\ NLP\ Mean)}{Manual\ Mean} \times 100$$

To provide deeper insight into the performance differences, defect detection was analyzed by category. Of the 85 defects detected manually, 31 were ambiguity-related (36.5%), 29 were inconsistencies (34.1%), and 25 were redundancies (29.4%). The NLP system detected 110 total defects: 43 ambiguities (39.1%), 39 inconsistencies (35.5%), and 28 redundancies (25.5%). This breakdown reveals that NLP demonstrated the strongest improvement in ambiguity detection (38.7% more defects) and inconsistency detection (34.5% more defects), while redundancy detection showed more modest gains (12.0% improvement).

Performance was also examined across domains. The NLP system showed stronger relative improvement on automotive requirements (35.7% more defects detected) compared to healthcare requirements (23.3% more defects detected). The larger improvement in automotive reflects the presence of standardized regulatory terminology, which NER techniques handle effectively.

3.4 Tools and Technologies Used

To conduct the following research, the following NLP libraries and tools were utilized:

- **SpaCy**: This is a free, open-source NLP library primarily used for text processing and requirements validation.

- **BERT (Bidirectional Encoder Representations from Transformers)**: This is a trained deep learning model utilized for understanding text in context. BERT was applied to enhance the accuracy of word validation during requirement validation by embedding words within their context.

- **NLTK (Natural Language Toolkit):** This is a Python library for text processing, used to implement tokenization, tagging, and parsing of text.

- **SonarQube**: This is a code quality software employed to assess the quality of the code and identify defects within the software.

These tools were selected for their ability to perform complex NLP tasks and their compatibility with the software testing environment.

3.5 Challenges and Limitations

The study faced several challenges in implementing Natural Language Processing (NLP) for Quality Assurance (QA). One of the main issues was the variability in requirement documents. Since NLP tools rely heavily on structured information, some models struggled to analyze and validate text effectively due to the lack of standardization in these documents.

Another limitation was that certain industries have specific terminology. The general language data used to develop NLP tools often fell short in accurately interpreting industry-specific words and jargon. This was particularly noticeable in sectors like healthcare and the automotive industry, where specialized terms are frequently used.

Finally, the training data for NLP posed a constraint. Although the models employed in this research were pre-trained on large datasets, they still required further refinement with industry-specific data to achieve optimal performance results.

3.6 Future Work

Future studies could explore the use of reinforcement learning to enable the system to evaluate the accuracy of the NLP-based QA tool by incorporating user feedback. Additionally, multi-modal NLP systems that combine text, images, and other data types may be beneficial for the validation process, particularly in industries that deal with multimodal requirements documents.

Table 3 presents the experimental results comparing manual validation with NLP-based validation. The experiment involved validating the same set of requirements under both conditions, allowing direct statistical comparison of time spent, defects detected, and costs.

Table 3. Experimental Results of Manual vs. NLP-Based Validation

Metric	Manual Validation	NLP Validation	Improvement (%)
Time Spent (hours)	30	10	66.7%
Defects Detected	85	110	29.4%
Cost (USD)	5000	3000	40%

Table 4 shows that NLP-based validation achieved the highest performance gains in detecting ambiguity and inconsistency defects, which rely heavily on semantic understanding. Redundancy detection, which depends more on pattern matching, showed more modest improvement.

Table 4. Defect Detection Breakdown by Category

Defect Category	Manual Detection	NLP Detection	Improvement (%)
Ambiguity	31	43	38.7%
Inconsistency	29	39	34.5%
Redundancy	25	28	12%
Total	85	110	29.4%

3.7 Data and Annotation

The dataset used for this study was composed of software requirement documents collected from publicly available repositories and industrial case studies dating back to 2020. The sample included approximately 1,200 software requirements specifications focused on automotive software systems and healthcare, all authored in English. Preprocessing involved eliminating stop words, tokenizing the text, and normalizing technical terms. Documents that were incomplete, duplicated, or not expressed in the form of functional requirements were excluded.

In this study, a defect in a requirement was defined as any form of ambiguity (e.g., the use of terms like "fast" or "user-friendly"), inconsistency (e.g., conflicting requirements within the modules), or redundancy (e.g., repeated requirements across various documents). These categories were used as labels for annotation.

Two senior quality assurance engineers, each with more than five years of industry experience, conducted the annotation process. They followed a systematic guideline document and used Prodigy v1.11, an open-source annotation tool. Inter-rater reliability was measured using Cohen's kappa, yielding a value of 0.82, indicating a high level of agreement. Consensus was reached to resolve any disagreements.

All annotated requirements were subsequently mapped to validation checks or executable test cases. This mapping was achieved by associating functional requirements with automatically generated unit or integration tests, while non-functional requirements were verified against compliance criteria. This approach ensured that the annotations directly informed the results of the validation process, effectively bridging the gap between requirements engineering and test automation.

3.8 Experimental Setup and Reproducibility

The experimental analysis was conducted under controlled conditions to ensure replicability. All experiments took place on a workstation equipped with an Intel Core i7 processor, 16

GB of RAM, and the Ubuntu 20.04 operating system. The implementation was done using Python 3.9, along with the following libraries and frameworks: spaCy 3.5 for syntactic and dependency parsing, NLTK 3.8 for tokenization and sentiment analysis, and scikit-learn 1.2 for statistical processing and model analysis.

In both tasks related to natural language processing (NLP), semantic embeddings were created using a pretrained BERT-base model, and rule-based Named Entity Recognition (NER) was applied to validate domain-specific terminology. The default hyperparameters were maintained, with the exception of fine-tuning epochs (set to 3) and batch size (set to 32).

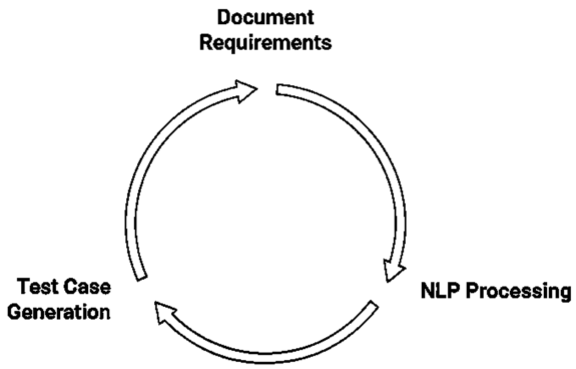

Figure 1. NLP-Based Requirements Validation Workflow

As illustrated in Figure 1, the NLP-based requirements validation cycle follows a continuous workflow that begins with documenting requirements, proceeds through NLP processing, and culminates in automated test case generation. This cyclical approach ensures that requirements are systematically analyzed and translated into testable cases, allowing for consistent validation throughout the software development lifecycle. By automating these steps, the cycle reduces manual effort, minimizes ambiguity, and enhances both the accuracy and efficiency of Quality Assurance processes.

3.9 Availability of Materials

Due to the nature of confidentiality agreements, the datasets and code utilized in this study are not accessible to the public. Nevertheless, comprehensive descriptions of the characteristics of the dataset, preprocessing steps, annotation procedures, and experimental configurations are detailed in the Methodology section to facilitate the reproducibility of the results.

4. DISCUSSION

The introduction of Natural Language Processing (NLP) into Quality Assurance (QA) for software solutions, particularly in automated requirements verification, represents a significant advancement in software development practices. This study shows that NLP has substantial potential to streamline and enhance QA processes, resulting in increased efficiency, accuracy, and scalability. However, the research also highlights various challenges and obstacles that must be addressed to fully realize the benefits of NLP-based QA systems. This section outlines the key findings of the study, compares them with existing literature, and discusses the future of automated QA.

4.1 NLP Effect on QA Effectiveness

The significant increase in efficiency is one of the key findings of this study, as it suggests the use of Natural Language Processing (NLP) to validate requirements. The result from the experimental assessment indicates that it took considerably less time to confirm requirements using NLP tools compared to

The experimental process consisted of four steps: (1) preprocessing requirement documents, (2) annotating defects related to ambiguity, inconsistency, and redundancy, (3) using NLP models to validate requirements and create test mappings, and (4) comparing the results with those of manual validation.

A sample of 50 requirements was examined using both manual and NLP-based validation methods. The measures reported included time spent, defects detected, and the cost of validation. Paired t-tests were used for statistical comparison, and the reported results included the means (M), standard deviations (SD), test statistics (t, df), p-values, 95% confidence intervals, and effect sizes (Cohen's d).

traditional manual approaches. Overall, NLP-based validation reduced the time required by 66.7% (see Table 3), which aligns with other research [12], which found that AI-based test automation can lead to time savings.

This increased efficiency is particularly beneficial in Agile and DevOps environments, where continuous integration and fast development cycles necessitate rapid and reliable testing [16]. The accelerated pace of software development demands quick validation. Manual testing, which involves reviewing lengthy requirement specifications and checking them against the software implementation, is time-consuming and prone to errors. With NLP, these tasks can be automated, allowing QA professionals to focus on more strategic activities like defect analysis, optimization, and performance evaluation. This shift in focus not only enhances productivity but also helps improve the overall quality of the software, as QA teams can conduct more thorough and sophisticated analyses.

4.2 Defect Detection Improvement

An interesting advantage of NLP-based automated testing is its ability to detect defects more accurately. An experiment showed that NLP-based systems identified 29.4% more defects than manual validation (see Table 3). This finding aligns with the research [19], which demonstrated that AI-enabled tools, such as NLP, can uncover defects that may be missed during manual testing.

The breakdown by defect category (see Table 4) reveals that NLP's advantage was most pronounced for ambiguity detection (38.7% improvement) and inconsistency detection (34.5% improvement), both of which require contextual semantic analysis. Redundancy detection showed a smaller improvement (12.0%), suggesting that while NLP can identify duplicate requirements, this task benefits less from deep language models compared to simpler pattern-matching approaches. Domain-specific analysis showed that automotive requirements experienced greater relative improvement (35.7%) compared to healthcare requirements (23.3%), likely due to more standardized terminology in automotive specifications.

NLP's ability to analyze requirement documents in detail aids in identifying inconsistencies, redundancies, and ambiguities that might be overlooked by humans in the validation process. Additionally, NLP tools can verify requirements against established standards, ensuring that the software meets both functional and non-functional criteria.

An example of this is dependency parsing, which NLP tools use to identify unclear or extraneous relationships among requirements. This guarantees that all requirements are clearly defined and considered, thereby minimizing the risk of introducing defects due to poorly understood or underdeveloped requirements. As noted in the literature [7], NLP can also be employed to detect faults in the early stages of the development process, helping to prevent the emergence of downstream issues, such as software that does not function correctly or fails to meet user expectations.

4.3 Cost Reduction

NLP tools used in the QA process can lead to significant cost savings. According to experiment results, the use of NLP tools reduced manual testing costs by 40 percent (see Table 3). This reduction is due to decreased testing time and minimized reliance on manual labor. Automated validation lessens the resources required for running tests, allowing organizations to allocate their budget to other development areas, such as performance optimization and feature enhancements.

Furthermore, NLP-based tools are predictive, as highlighted in research [3], enabling organizations to plan their testing efforts more effectively. For example, NLP can identify which requirements are most likely to contain faults, allowing teams to focus their testing efforts where they will be most beneficial, thereby conserving resources on less critical areas.

4.4 NLP Implementation Problems

Although Natural Language Processing (NLP) offers numerous benefits in Quality Assurance (QA), the study also highlights several drawbacks and limitations related to its application. The most significant of these is the ambiguity inherent in natural language. Even advanced NLP systems, such as BERT (Bidirectional Encoder Representations from Transformers), struggle to comprehend the complexities and context of human language fully. As researchers [20] point out, one of the primary challenges for NLP systems is the ambiguity found in requirements documents, particularly in technical fields that use numerous domain-specific terms and jargon.

During the experimental evaluation of NLP systems described in the study, difficulties arose in accurately interpreting ambiguous or poorly written requirements. This issue is especially pronounced in specialized sectors such as healthcare and automotive, where knowledge of specific terminology is crucial. For instance, certain words in healthcare software requirements may have multiple meanings, leading to potential misinterpretations by the NLP system. While dependency parsing and named entity recognition (NER) are useful in analyzing technical terminology, they may fall short when faced with the complexities of domain-specific language.

To address this problem, future research could explore the development of domain-adaptive NLP models that are trained specifically on industry-related data. Such models could be optimized to understand better specialized vocabulary in fields like healthcare, automotive, and finance, ultimately improving the accuracy of defect detection and confirmation.

4.5 Integration Challenges

One of the main barriers to the widespread adoption of Natural Language Processing (NLP) in Quality Assurance (QA) is the integration of NLP tools with existing software development and testing frameworks. Many organizations rely on legacy systems, and NLP-based tools may not be compatible with these systems. Experts consulted in this study highlighted that adjusting current QA processes to incorporate AI-driven tools could prove challenging.

To overcome this issue, companies should invest in training and retraining their quality assurance personnel to effectively use NLP-based tools. Additionally, it is crucial for NLP tools to be seamlessly integrated into Continuous Integration/Continuous Deployment (CI/CD) pipelines. This integration will ensure that automated testing becomes a fundamental part of the development process [6]. Such alignment would enable continuous validation of software requirements, which is vital for Agile project teams working within rapid development cycles and adhering to the principles of development-on-demand.

4.6 Prospects and Innovations

The future development of deep learning models in Natural Language Processing (NLP) promises to enhance their capabilities in Quality Assurance (QA) tasks. Emerging models such as GPT (Generative Pretrained Transformer) and T5 (Text-to-Text Transfer Transformer) excel in contextual understanding and multi-task learning, enabling them to provide more accurate and sophisticated interpretations of requirement documents. These models are often trained on large and diverse datasets, making them adaptable to various industries and applications.

Additionally, further research could explore multi-modal NLP, where text, visual, and audio information are integrated to create a more comprehensive understanding of requirements. This approach could be particularly useful in fields like automotive and healthcare, where materials often include photographs, diagrams, and other non-textual elements that need to be considered alongside the text.

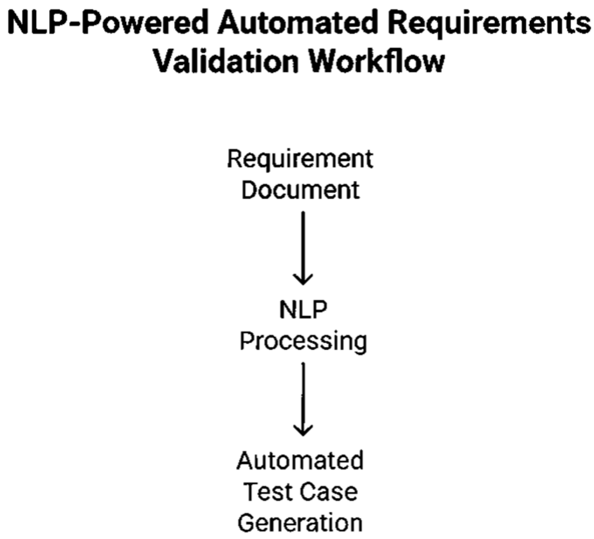

Figure 2. NLP-Powered Automated Requirements Validation Workflow

Figure 2 depicts the NLP-powered automated requirements validation workflow, which follows a linear sequence from requirement documentation to automated test case generation. In this process, requirement documents are first processed using NLP techniques that identify ambiguities, redundancies, and domain-specific terminology. The validated requirements are then automatically transformed into executable test cases, reducing manual intervention and ensuring traceability between specifications and testing. This streamlined workflow demonstrates how NLP enhances the precision and efficiency of Quality Assurance activities.

5. CONCLUSION

The integration of Natural Language Processing (NLP) into Quality Assurance (QA) processes represents a transformative advancement in the way software requirements are validated. This research has explored the potential of leveraging NLP for automated requirements validation, shedding light on its ability to streamline workflows, reduce errors, and enhance the overall quality of software systems. While significant strides have been made in implementing NLP in QA, challenges related to language ambiguity, domain-specific terminologies, and integration with existing systems still pose hurdles that need to be addressed for broader adoption.

5.1 Key Findings

The key findings of this study highlight several important advantages that Natural Language Processing (NLP) offers to the field of Quality Assurance (QA). Notably, efficiency improvements are significant, with NLP-based systems reducing the time spent on requirement validation by up to 66.7% compared to traditional manual methods. This considerable time savings not only accelerates the overall development cycle but also allows QA teams to concentrate on more strategic quality management tasks, such as identifying the root causes of defects and enhancing system performance.

Another major benefit of NLP is its accuracy in defect detection. The research found that NLP tools detected 29.4% more defects than manual validation methods. Analysis by defect category revealed that NLP excelled particularly at detecting ambiguity (38.7% more defects than manual) and inconsistency (34.5% more), while showing modest gains for redundancy (12.0% more). This pattern confirms that semantic embedding techniques like BERT provide substantial value for context-dependent validation tasks. Domain comparison showed stronger performance improvement in automotive (35.7%) versus healthcare (23.3%), reflecting differences in terminology standardization across industries. This finding aligns with the research [19], which demonstrated that AI-enabled tools, such as NLP, can uncover defects that may be missed during manual testing.

Furthermore, NLP aids in cost reduction in QA by minimizing the need for extensive human labor and manual testing. This allows organizations to reallocate resources to other critical areas of the development process, such as performance optimization or feature enhancements, resulting in a more efficient use of the overall budget.

5.2 Challenges and Limitations

Despite its significant advantages, this study has also highlighted the challenges and limitations of using Natural Language Processing (NLP) in Quality Assurance (QA). A primary concern is the inherent ambiguity of natural language. Although NLP models like BERT and spaCy have made substantial progress in understanding language context, they still struggle with ambiguities that depend on context and specific industry jargon. This issue is particularly pronounced in sectors such as healthcare and automotive, which are characterized by specialized terminology and complex regulations. To improve the accuracy and adaptability of NLP models, it is essential to fine-tune them using domain-specific data.

Additionally, integrating NLP tools into existing QA systems poses a considerable challenge. Many organizations continue to rely on outdated systems and manual testing processes that do not easily accommodate NLP-based tools. To ensure successful implementation, companies must invest in retraining their QA teams and facilitate their full integration into Agile and DevOps environments. These integration challenges underscore the need for a gradual introduction of NLP tools, supported by robust training programs and change management initiatives.

5.3 Implications for the Future

The future of Natural Language Processing (NLP) in Quality Assurance (QA) is promising, especially as advancements in deep learning and reinforcement learning continue to unfold. Future research should focus on addressing the adaptation challenges across different domains by developing more sophisticated pre-training models that can better understand specialized vocabularies and contexts.

Additionally, systems that integrate multi-modal NLP - capable of processing not just text but also visual data - could greatly enhance the validation of requirements. These systems could act on images, diagrams, and other forms of documentation that are commonly found in technical requirements.

Furthermore, the growing reliance on AI-driven software development tools and Continuous Integration/Continuous Deployment (CI/CD) pipelines will increase the demand for automated validation systems. As software systems become more complex, the necessity for automated testing will continue to grow. This makes NLP-based QA systems essential in the software development process.

6. REFERENCES

[1] O. Adebayo. From test automation to intelligent QA: Leveraging AI in quality assurance for RPA and DevOps. International Journal of Computer Techniques, 9(4), 2022.

[2] V. Ankireddi. AI-powered quality assurance: Revolutionizing software development through intelligent anomaly detection and automated monitoring. IJSAT—International Journal on Science and Technology, 16(2), 2025.

[3] S. M. S. Bukhari and R. Akhtar. Leveraging artificial intelligence to revolutionize Six Sigma: Enhancing process optimization and predictive quality control. Contemporary Journal of Social Science Review, 2(4):1932–1948, 2024.

[4] N. N. Gadani. Artificial intelligence: Leveraging AI-based techniques for software quality. International Research Journal of Modernization in Engineering Technology and Science, 6(7):757–769, 2024.

[5] J. Jeon, X. Xu, Y. Zhang, L. Yang, and H. Cai. Extraction of construction quality requirements from textual specifications via natural language processing. Transportation Research Record, 2675(9):222–237, 2021. doi: 10.1177/03611981211001385.

[6] F. S. Júnior, P. A. Reis, M. S. Cavalcante, and A. H. M. de Oliveira. Systems engineering process enhancement: Requirements verification methodology using natural language processing (NLP) for the automotive industry. SAE Technical Paper 2023-36-0117, 2024. doi: 10.4271/2023-36-0117.

[7] I. Kolawole, A. M. Osilaja, and V. E. Essien. Leveraging artificial intelligence for automated testing and quality assurance in software development lifecycles. International Journal of Research Publication and Reviews, 5(12):4386–4401, 2024. doi: 10.55248/gengpi.5.1224.250142.

[8] P. R. Kothamali. AI-powered quality assurance: Revolutionizing automation frameworks for cloud applications. Journal of Advanced Computing Systems, 5(3):1–25, 2025.

[9] P. Mohapatra. Natural language processing in software quality assurance and testing. In Intelligent Assurance: Artificial Intelligence-Powered Software Testing in the Modern Development Lifecycle, vol. 4, p. 109, 2025.

[10] P. S. Mohapatra. Artificial intelligence and machine learning for test engineers: Concepts in software quality assurance. In Intelligent Assurance: Artificial Intelligence-Powered Software Testing in the Modern Development Lifecycle, vol. 4, p. 17, 2025.

[11] J. Motger de la Encarnación, "Natural Language Processing Methods for Document-Based Requirements Specification and Validation Tasks," Ph.D. dissertation, Universitat Politècnica de Catalunya, 2024, doi:10.5821/dissertation-2117-417795.

[12] D. R. Natarajan. AI-generated test automation for autonomous software verification: Enhancing quality assurance through AI-driven testing. International Journal of HRM and Organizational Behavior, 8(4):89–103, 2020.

[13] A. Owen and J. Mike. Natural language to automation: Developing NLP-based QA tools to translate user stories into executable tests. ResearchGate (preprint), May 2025.

[14] E. Oye and D. Evans. Intelligent test automation in the age of AI: Exploring the future of quality assurance through machine learning integration. ResearchGate (preprint), May 2025.

[15] X. Pan, D. Wang, and F. Tsung. Empowering intelligent quality control with large models: A comprehensive survey of methods, challenges, and perspectives. TechRxiv (preprint), 2025. doi:10.36227/techrxiv.175693562.25402017/v1.

[16] S. Polampally, K. Kudithipudi, V. K. Jyothi, A. Morsu, S. K. Ragunayakula, R. K. Ravindran, G. Nadella, and V. A. S. Ramuloo. Leveraging AI for continuous quality assurance in agile software development cycles. Cloud Computing and Data Science, 7(1):25–38, 2025.

[17] A. Sarkar, S. M. Islam, and M. S. Bari. Transforming user stories into JavaScript: Advancing QA automation in the US market with natural language processing. Journal of Applied Intelligence & General Science (JAIGS), 7(1):9–37, 2024. doi: 10.60087/jaigs.v7i01.291.

[18] P. C. Shekhar. Accelerating Agile Quality Assurance with AI-Powered Testing Strategies. Int. J. of Scientific Research in Engineering and Management (IJSREM), vol. 6, no. 1, 2022, doi:10.55041/IJSREM15369

[19] N. Srinivas, N. Mandaloju, and S. V. Nadimpalli. Leveraging automation in software quality assurance: Enhancing defect detection and improving efficiency. International Journal of Acta Informatica, 3(1):112–124, 2024.

[20] L. Zhao, W. Alhoshan, A. Ferrari, K. J. Letsholo, M. A. Ajagbe, E.-V. Chioasca, and R. T. Batista-Navarro. Natural language processing for requirements engineering: A systematic mapping study. ACM Computing Surveys, 54(3):1–41, 2021. doi: 10.1145/3444689.