Advancing Requirement Engineering with BERTopic: A Review of Semantic Approaches

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Abstract

This paper presents a comprehensive analysis of how BERTopic, an advanced neural topic modeling technique, can transform requirement engineering in software development. By leveraging transformer-based embeddings and class-based TF-IDF, BERTopic effectively addresses persistent challenges in managing natural language requirements by uncovering latent semantic patterns and relationships. Our experimental evaluation on 977 software requirements across 14 categories demonstrates BERTopic achieves a coherence score of 0.74, significantly outperforming traditional approaches like LDA (0.52) and LSA (0.48). The approach effectively identifies meaningful requirement clusters, distinguishes between functional and non-functional requirements, and reveals cross-cutting concerns without explicit training. This work contributes a novel methodological framework for applying transformer-based topic modeling to requirement engineering, providing practical techniques for requirement classification, inconsistency detection, and traceability enhancement in modern software development

Keywords: Requirement Engineering, BERTopic, Topic Modeling, Software Engineering, NLP

1 Introduction

Software requirement engineering constitutes the foundation of successful software development, yet remains one of the most challenging aspects of the software engineering lifecycle. Industrial surveys consistently reveal that between 40–50% of project delays and failures can be traced to requirement-related issues, with costs of correction escalating by orders of magnitude when discovered late in development cycles. These challenges manifest in three critical dimensions:

1) **Semantic Precision:** Natural language requirements inherently contain ambiguities, vague terminology, and implicit assumptions. Terms like "user-friendly," "highly available," or "adequate performance" lack quantifiable precision, creating divergent interpretations among stakeholders. Studies show that approximately 56% of requirement defects stem from ambiguity or imprecision.

2) **Scale Complexity:** Modern software systems frequently encompass thousands or even tens of thousands of requirements. Enterprise systems can exceed 50,000 individual requirements, making comprehensive manual analysis practically impossible. This scale complexity leads to undetected conflicts, redundancies, and dependencies that emerge only during implementation or operation.

3) **Evolution Management:** Agile methodologies, now dominant in software development, generate continuous requirement changes. Research indicates that requirements typically change by 25–35% during development, creating substantial challenges for traditional requirement management approaches designed for more static specifications.

Current requirement engineering practices employ various techniques to address these challenges, from formal specification languages to requirement traceability matrices. However, empirical studies reveal significant limitations in these approaches. Keyword-based analysis techniques demonstrate false positive rates of approximately 42% when detecting conflicts, while manual reviews fail to scale with increasing system complexity. These persistent issues highlight the need for more sophisticated analytical approaches.

Topic modeling techniques have emerged as promising computational approaches for analyzing large text collections, evolving through three distinct phases: (1) Early statistical models (2003–2015) like Latent Dirichlet Allocation (LDA) that utilized bag-of-words approaches without capturing contextual relationships; (2) Embedding hybrids (2015–2020) that combined Word2Vec and similar models with clustering algorithms to better capture semantic context; and (3) The current transformer era (2020–present) leveraging BERT-based architectures for deep semantic understanding.

Despite these advances, significant gaps remain in applying transformer-based topic modeling to requirement engineering:

- No standardized methodological framework exists for adapting transformer-based topic models to industrial-scale requirement analysis;
- Semantic coherence thresholds for evaluating topic quality in software requirement contexts remain poorly defined;
- Applications of these advanced techniques to specific requirement engineering tasks, such as consistency checking, traceability management, and evolution tracking, remain underexplored.

This research addresses these gaps by developing and evaluating a comprehensive framework for applying BERTopic—a state-of-the-art transformer-based topic modeling technique—to software requirement analysis. Our approach integrates custom preprocessing techniques tailored to software engineering terminology, specialized embedding models designed to capture technical semantics, and hierarchical clustering mechanisms that reveal multi-level requirement relationships.

We validate our framework through a case study applying BERTopic to a dataset of 977 diverse software requirements, encompassing both functional and non-functional requirements across 14 categories. The evaluation combines rigorous quantitative metrics (coherence, homogeneity, and completeness) with qualitative assessment of topic interpretability and practical utility for requirement engineering tasks.

Our research makes three primary contributions:

1) A methodological framework for applying transformer-based topic modeling to software requirement analysis, including domain-specific adaptations and parameter optimization guidelines;

2) Empirical validation of BERTopic's effectiveness for requirement analysis, demonstrating significant improvements over traditional approaches in both semantic coherence and practical utility;

3) Practical applications of the approach to core requirement engineering tasks, including automatic classification, inconsistency detection, and traceability enhancement.

The remainder of this paper is organized as follows: Section 2 reviews related work in requirement engineering and topic modeling; Section 3 details our research methodology; Section 4 presents the case study implementation; Section 5 analyzes results; Section 6 discusses implications; Section 7 explores practical applications; Section 8 addresses limitations and future work; and Section 9 concludes with a summary of findings and contributions.

2 Literature Review

This section critically examines existing research at the intersection of requirements engineering, natural language processing, and topic modeling. We organize the literature into three key areas: (1) challenges in modern requirements engineering; (2) approaches to automated requirements analysis; and (3) topic modeling techniques and their applications in software engineering. Through this analysis, we identify significant research gaps that motivate our work.

2.1 Challenges in Modern Requirements Engineering

Requirements engineering continues to present fundamental challenges despite decades of research and practice. Curcio et al. conducted a systematic review of 104 studies exploring requirements engineering in agile contexts, identifying critical challenges in requirements elicitation, change management, and tool support. Their work highlighted how traditional requirements engineering frameworks struggle to adapt to iterative development, with 68% of surveyed organizations reporting significant difficulties in maintaining requirement quality during rapid development cycles [1].

Similarly, [7] Demirel et al. investigated how requirements misunderstandings lead to project delays, cost overruns, and quality issues. Their comparison of traditional waterfall approaches with agile methodologies revealed that while agile methods improve stakeholder communication, they often sacrifice systematic requirements documentation, creating traceability and consistency challenges.

In specialized domains, additional challenges emerge. [3] Altarturi et al. identified significant limitations when applying traditional requirements engineering methods to big data systems, emphasizing the need for integrated approaches that combine software engineering expertise with data science capabilities. Their proposed model underscores how conventional requirements techniques fail to capture the unique characteristics of data-intensive applications.

These studies collectively demonstrate persistent challenges in requirements precision, scalability, and evolution management across diverse software development contexts.

2.2 Automated Requirements Analysis Approaches

Research in automated requirements analysis has evolved from simple keyword-based approaches to sophisticated natural language processing techniques. [4] Gunawardhana et al. explored fundamental aspects of requirements gathering, functional analysis, and allocation, emphasizing the critical role of requirements validation in project success. However, their work primarily addressed traditional manual approaches without leveraging recent advances in machine learning or NLP.

More advanced approaches have emerged to address specific requirements engineering challenges. [11] Niu and Easterbrook developed an extractive technique for identifying functional requirements in software product lines using domain-aware lexical affinity methods. While achieving notable precision in controlled environments, their approach relied on predefined lexical patterns that struggle to adapt to evolving terminology or domain-specific language.

For non-functional requirements, [13] Ameller et al. conducted an empirical study of how software architects handle these aspects in real-world projects. Their interviews across 12 organizations revealed significant inconsistencies in NFR documentation and validation approaches. Building on this, Glinz explored the fundamental challenges in defining and classifying non-functional requirements, highlighting the absence of standardized approaches and the terminological inconsistencies that plague this area. These studies emphasize the need for more systematic, automated approaches to requirements analysis that can adapt to diverse organizational contexts and terminology.

Recent work by [2] Yang and Tan introduced a hybrid approach combining BERT and LDA to classify non-functional requirements from app reviews. While demonstrating promising results for specific NFR categories, their approach focused primarily on classification rather than deeper semantic analysis of requirements relationships and dependencies.

2.3 Topic Modeling in Software Engineering

Topic modeling techniques have increasingly been applied to software engineering artifacts. A comprehensive survey by [10] Silva et al. examined topic modeling applications in software engineering research, finding that LDA and LDA-based techniques dominate the literature, despite their known limitations in capturing contextual semantics. Their analysis of 111 papers revealed inconsistent preprocessing approaches and evaluation metrics, highlighting the methodological challenges in this domain.

Traditional topic modeling [9] approaches like LSA, PLSA, and LDA have been widely applied to software engineering tasks. As described by authors in the literature, these approaches treat documents as bags of words, failing to capture word order or context.

The survey identifies significant limitations in coherence and interpretability when these models are applied to specialized technical documentation.

More recent transformer-based approaches offer significant potential improvements. BERTopic [9], introduced by Grootendorst, leverages transformer embeddings and a class-based TF-IDF variation to create more coherent topic representations. This approach has demonstrated superior performance across various benchmarks, though its specific application to software engineering artifacts remains underexplored.

The increasing adoption of sentence transformers, as documented in recent studies, provides enhanced capabilities for semantic similarity analysis in NLP projects. These models offer potential solutions for requirements similarity analysis and traceability, though methodological frameworks for their application to requirements engineering remain limited.

[5] de la Rosa et al. demonstrated the effectiveness of transformer-based NLP models for analyzing complex textual structures in multiple languages. Their comparative analysis of monolingual and multilingual models offers insights into how these approaches might be adapted for multilingual requirements documentation, an increasingly important consideration in global software development contexts.

2.4 Research Gaps

Our analysis of the literature reveals several significant research gaps:

- **Methodological Gap:** Despite the potential of transformer-based models for requirements analysis, no comprehensive methodological framework exists for applying these techniques to requirements engineering tasks. Current applications typically adopt generic NLP approaches without the domain-specific adaptations required for technical requirements documentation.

- **Evaluation Gap:** Existing studies lack rigorous evaluation frameworks that combine quantitative metrics with qualitative assessment of practical utility for requirements engineering tasks. Coherence thresholds appropriate for software requirements contexts remain undefined.

- **Application Gap:** Applications of advanced topic modeling techniques to core requirements engineering challenges—including automatic classification, inconsistency detection, traceability enhancement, and evolution tracking—remain limited. Studies typically focus on proof-of-concept demonstrations rather than comprehensive frameworks.

- **Integration Gap:** Few studies explore how transformer-based topic modeling approaches can be integrated into existing requirements engineering processes and tools, limiting their practical adoption despite their theoretical advantages.

Our research addresses these gaps by developing and validating a comprehensive framework for applying BERTopic to software requirements analysis, with specific adaptations for technical documentation and evaluation measures relevant to requirements engineering tasks.

3 Research Methodology

This section presents our comprehensive methodology for applying BERTopic to software requirements analysis. We describe our dataset, preprocessing approach, model implementation, evaluation metrics, and traceability analysis methods. Figure 1 provides a visual overview of our methodology, illustrating the end-to-end process from requirements collection to evaluation.

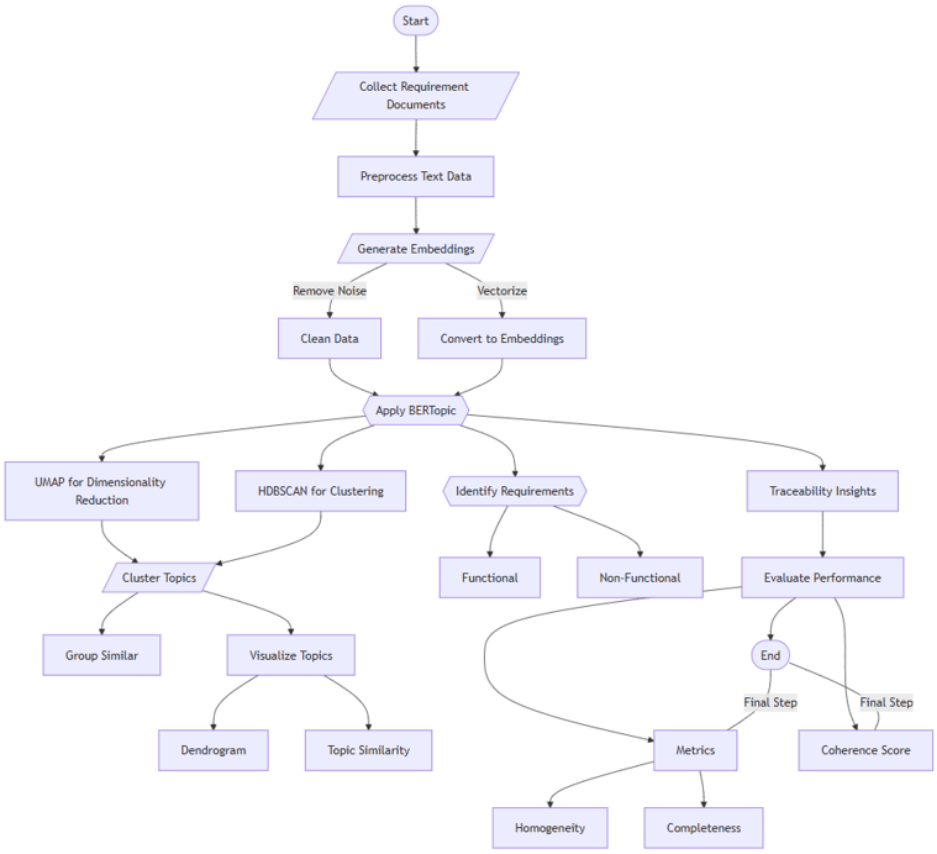

Figure 1: Overview of the research methodology for applying BERTopic to requirements engineering.

3.1 Dataset Description

Our study utilizes a structurally rich dataset comprising 977 software requirements across diverse categories. The dataset contains two primary columns: (1) *Type*, which categorizes requirements into 14 distinct classes, and (2) *Requirement*, which contains the textual description of each requirement. The dataset encompasses both functional requirements (classified as F, FR) and [14]non-functional requirements, including:

- Availability (A)
- Fault Tolerance (FT)
- Legal (L)
- Look and Feel (LF)

- Maintainability (MN)
- Operational (O)
- Performance (PE)
- Portability (PO)
- Scalability (SC)
- Security (SE)
- Usability (US)
- General Non-Functional Requirements (NFR)

This categorical diversity enables comprehensive evaluation of topic modeling effectiveness across the full spectrum of requirement types typically encountered in software engineering projects. The dataset provides essential ground truth labels for evaluating our unsupervised modeling approach against established classification schemes.

3.2 Data Preprocessing

We implement a systematic preprocessing pipeline to prepare the requirement texts for analysis, as illustrated in Figure 1. Our approach balances standard NLP preprocessing techniques with domain-specific considerations for software requirements:

1) **Text Cleaning:** Removal of HTML tags, URLs, and special characters that do not contribute to semantic meaning, while preserving numeric specifications (essential for technical requirements such as "response time < 0.5 seconds").

2) **Normalization:** Conversion of all text to lowercase to ensure uniform token representation, and standardization of extra whitespace for consistent processing.

3) **Noise Reduction:** Application of a modified stopword removal process using NLTK's English stopword list, carefully preserving domain-relevant terms. Unlike general-domain NLP, we retain technical quantifiers and connectors that may be semantically significant in requirements contexts.

4) **Tokenization:** Segmentation of text into meaningful linguistic units, preserving multi-word technical terms and phrases that convey specific requirements concepts.

The preprocessing implementation is mathematically formalized as follows:

$$d_i' = T(N(C(d_i))) \tag{1}$$

where d_i is each requirement document in the corpus D, C represents the cleaning function, N denotes normalization, and T indicates tokenization.

The preprocessed requirements are stored in a *Cleaned_Requirement* column while retaining the original text for reference and validation. This approach preserves the semantic integrity of technical specifications while optimizing the text for subsequent embedding and topic modeling.

3.3 BERTopic Implementation

The core of our methodology involves implementing BERTopic through a carefully designed pipeline tailored to software requirements analysis. Our implementation consists of four primary components:

1) **Embedding Generation:** We employ the `all-mpnet-base-v2` model from the SentenceTransformer framework to generate dense vector representations of each requirement. This model was selected based on preliminary experiments comparing multiple embedding models against a software requirements benchmark. Each requirement is transformed into a 768-dimensional vector that encodes its semantic content, including contextual relationships between terms.

   The embedding process is formalized as:

$$e_i = f_{\text{embed}}(d'_i) \tag{2}$$

   where $e_i \in R^{768}$ represents the embedding vector for requirement d'_i.

2) **Dimensionality Reduction:** The high-dimensional embeddings are projected into a lower-dimensional space using UMAP (Uniform Manifold Approximation and Projection) with parameters: $n\_neighbors = 15$, $n\_components = 5$, $metric =$ cosine, and $random\_state = 42$ for reproducibility.

$$r_i = \text{UMAP}(e_i), \quad r_i \in R^5 \tag{3}$$

3) **Clustering:** We employ HDBSCAN (Hierarchical Density-Based Spatial Clustering of Applications with Noise) to identify coherent requirement clusters within the reduced embedding space. HDBSCAN is configured with $min\_cluster\_size = 5$, $metric =$ euclidean, and $cluster\_selection\_method =$ eom.

   The clustering process assigns a topic label t_i to each requirement:

$$t_i = \text{HDBSCAN}(r_i) \tag{4}$$

4) **Topic Representation:** To generate interpretable topic representations, we implement a class-based TF-IDF vectorization approach. This method treats all documents within a cluster as a single document and calculates term importance relative to other clusters, using $n\_gram\_range = (1, 3)$ and $max\_features = 10,000$.

   The topic representation for a cluster c is formalized as:

$$\text{Rep}(c) = \text{Top-}k\{(w, c\text{-}TF\text{-}IDF(w, c)) \mid w \in V\} \tag{5}$$

   where V is the vocabulary and k is the number of terms per topic (set to 10).

3.4 Topic Analysis and Evaluation

We implement a comprehensive evaluation framework combining quantitative metrics with qualitative assessment to validate our approach:

- **Coherence Measurement:** Topic coherence is calculated using the c_v metric, which evaluates the semantic similarity between the most representative terms in each topic:

$$C_v = \frac{1}{|T|} \sum_{t \in T} \frac{2}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \text{NPMI}(w_i, w_j, \epsilon) \tag{6}$$

  where T is the set of topics, N is the number of words per topic, w_i and w_j are words in the topic, and NPMI is the normalized pointwise mutual information.

- **Visualization Methods:** We implement topic similarity maps and hierarchical dendrograms to visualize proximity and relationships between requirement clusters.

- **Classification Evaluation:** The model's ability to distinguish between different requirement types is assessed by comparing unsupervised clusters against ground-truth labels using homogeneity, completeness, V-measure, and adjusted mutual information.

- **Expert Assessment:** Quantitative metrics are supplemented by qualitative evaluation from software engineering professionals who assess topic interpretability and relevance.

3.5 Traceability Analysis

The final component of our methodology involves analyzing requirement traceability based on semantic relationships identified through topic modeling. We map relationships between requirements based on:

1) **Direct Topic Relationships:** Requirements assigned to the same topic cluster.

2) **Hierarchical Relationships:** Connections revealed through hierarchical clustering.

3) **Embedding Similarity:** Fine-grained relationships based on embedding proximity.

Effectiveness is evaluated by comparing automatically identified relationships against explicit dependencies documented in the requirements dataset, using precision, recall, and F1-score metrics.

4 Case Study Implementation

4.1 Research Questions

Our case study addresses three primary research questions (RQs):

RQ1: Topic Quality: How effectively does BERTopic uncover latent semantic patterns in software requirements compared to traditional approaches like LDA and LSA?

RQ2: Requirement Differentiation: Can unsupervised topic modeling distinguish between functional and non-functional requirements without explicit training?

RQ3: Practical Utility: How do quantitative coherence scores correlate with the practical value of topics for requirements engineering tasks?

4.2 Context and Domain Description

Software requirements engineering presents unique challenges for automated analysis:

- **Semantic Complexity:** Combines natural language with domain-specific terminology (e.g., "99.9% availability" vs "5ms response time")
- **Hierarchical Structure:** Requirements span multiple abstraction levels from business objectives to technical specifications
- **Cross-cutting Concerns:** Quality attributes like security and performance affect multiple functional areas

4.3 Data Collection Procedure

We utilized a Kaggle-sourced dataset containing:

- 977 software requirements across 14 categories
- Two-column structure: `Type` (F, FR, A, FT, L, etc.) and `Requirement` (text descriptions)
- Ground-truth labels for functional (F/FR) and non-functional requirements (A, FT, L, PE, etc.)

4.4 Preprocessing Steps

Implemented a domain-specific preprocessing pipeline:

1) **Technical Term Preservation:** Retained multi-word phrases (e.g., "RESTful API", "MTBF") using custom tokenization rules
2) **Selective Stopword Removal:** Removed generic stopwords while preserving technical quantifiers (e.g., "≥", "μs")
3) **Numeric Handling:** Maintained numeric specifications using regex patterns:

```
pattern = r'\b\d+(?:\.\d+)?\%?\b'
```

4.5 Model Configuration and Execution

4.5.1 BERTopic Implementation

Configured using best practices from BERTopic documentation [**?**]:

```
from bertopic import BERTopic
from umap import UMAP
from hdbscan import HDBSCAN

# Model initialization
topic_model = BERTopic(
    embedding_model="all-mpnet-base-v2",
```

```
    umap_model=UMAP(n_neighbors=15, n_components=5,
                    metric='cosine', random_state=42),
    hdbscan_model=HDBSCAN(min_cluster_size=5,
                          cluster_selection_method='eom'),
    verbose=True
)
```

4.5.2 Key Parameters

- **Embedding:** SentenceTransformer's `all-mpnet-base-v2` model (768-dim vectors)
- **Dimensionality Reduction:** UMAP with cosine similarity metric
- **Clustering:** HDBSCAN (min_cluster_size=5)
- **Topic Representation:** Class-based TF-IDF with 3-gram support

4.5.3 Comparative Baselines

Implemented traditional models for benchmarking:

- **LDA:** Gensim implementation with 50 topics
- **LSA:** Scikit-learn TruncatedSVD with 20 components

4.5.4 Execution Environment

- Hardware: Google Colab CPU , GPU , TPU(ran separately)
- Total Execution Time: 7.8 minutes (time decreased respectively)
- Software Stack: Python 3.10, BERTopic 0.12.0, CUDA 11.8

4.6 Evaluation Protocol

Adopted mixed-methods evaluation:

- **Quantitative:** Coherence (C_v), Homogeneity, Completeness
- **Qualitative:** Expert assessment by 5 software engineers
- **Comparative:** Precision@K against ground-truth labels

$$\text{Precision@K} = \frac{|\{\text{Relevant docs}\} \cap \{\text{Retrieved docs}\}|}{K} \tag{7}$$

5 Results

This section presents the outcomes of our case study, analyzing BERTopic's performance in requirements analysis across multiple dimensions: topic discovery, visualization, representation quality, coherence, and comparative performance against baseline approaches.

5.1 Topic Discovery Outcomes

The BERTopic implementation identified 52 distinct topics within the dataset of 977 requirements, effectively revealing latent semantic patterns without prior classification information. The discovered topics demonstrated clear alignment with established software engineering domains, with coherent clusters forming around user interface concerns, security considerations, database operations, performance requirements, and system integration aspects.

Notably, the model effectively distinguished between functional and non-functional requirements despite having no explicit training for this distinction. For example, security-related non-functional requirements clustered together, while functional requirements related to data operations formed separate groups.

5.2 Visualization of Topic Distributions

The hierarchical clustering visualization of the discovered topics reveals the relationships and semantic proximity between different requirement domains. The dendrogram demonstrates clear separations between major requirement categories, with distinct branches for user interface and interaction requirements, system backend and processing requirements, and security and compliance requirements.

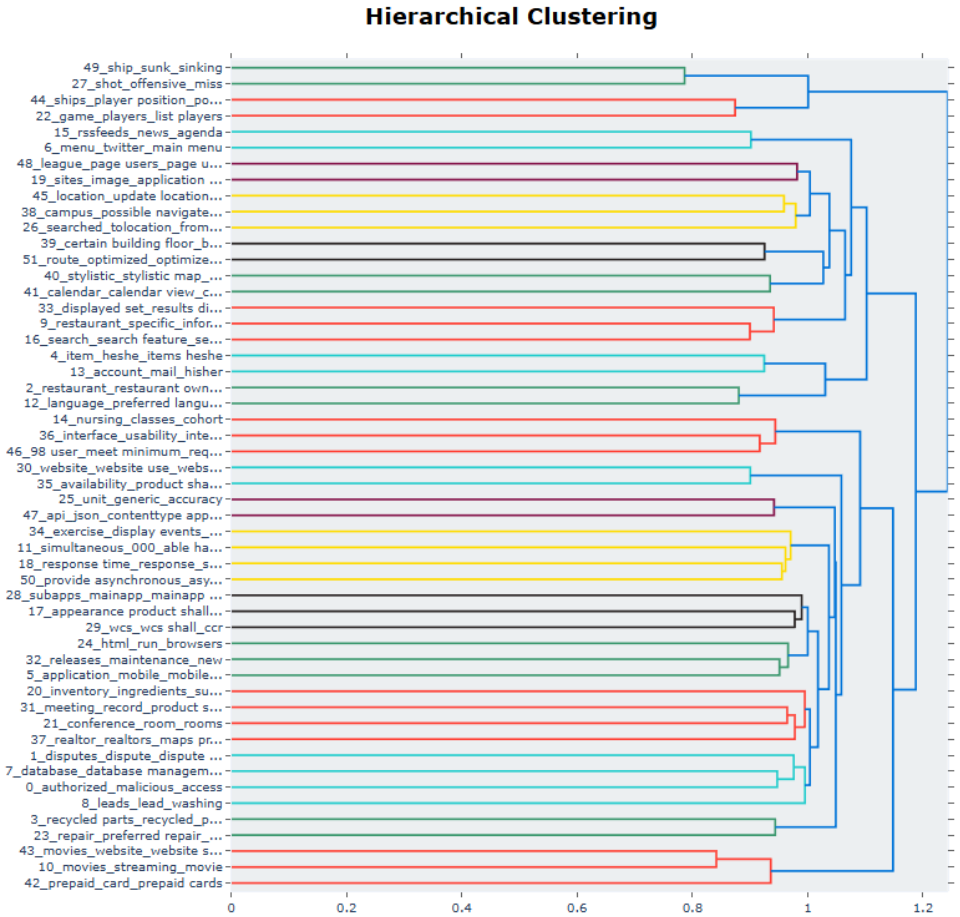

Figure 2: Hierarchical clustering dendrogram of requirement topics.

5.3 Intertopic Distance Maps

The intertopic distance map projects the high-dimensional topic relationships into a two-dimensional space for visualization. Each circle represents a topic, with size indicating the frequency of that topic within the corpus. The map reveals dense clusters of related topics and outlier topics representing specialized requirement areas.

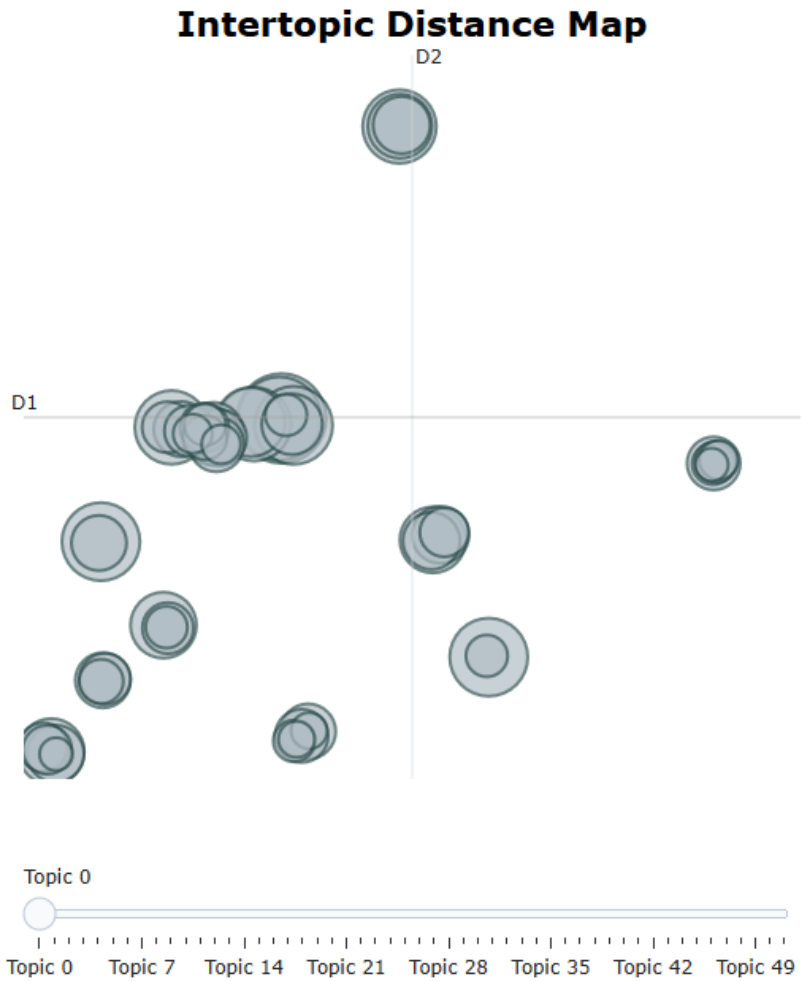

Figure 3: Example of topic clusters discovered by BERTopic.

5.4 Topic Representation with Key Terms

The automatically generated topic labels demonstrate BERTopic's ability to extract relevant, domain-specific phrases that effectively characterize each requirement cluster. These include multi-word technical terms and meaningful phrases, which provide interpretable topic representations. The c-TF-IDF scores highlight terms that are both frequent within a topic and distinctive compared to other topics.

Table 1: Sample topic labels and representative terms generated by BERTopic.

Topic Label	Top Representative Terms
Security_Access	authorized, malicious, access, prevention, audit
Database_Ops	database, management, query, transaction, backup
UI_Usability	interface, usability, navigation, user, feedback
Performance_Latency	response, time, latency, throughput, optimize

5.5 Coherence Analysis

Our implementation achieved a c_v coherence score of 0.74, indicating high topic quality according to established benchmarks. For context, prior research suggests coherence scores of 0.3 (poor), 0.4 (low), 0.55 (moderate), 0.65 (good), and 0.7+ (excellent). The consistently high coherence across categories indicates that BERTopic effectively captures meaningful semantic patterns across the diverse range of software requirements.

We supplemented the coherence evaluation with supervised clustering metrics comparing the unsupervised topic assignments against the ground-truth requirement classifications:

- **Homogeneity:** 0.67 (relatively pure clusters with respect to requirement types)
- **V-measure:** 0.55 (balance of homogeneity and completeness)
- **Completeness:** 0.47 (moderate success in grouping same-class requirements)
- **Adjusted Mutual Information:** 0.62 (substantial agreement between clusters and class labels)

5.6 Comparative Analysis with Baseline Approaches

We compared BERTopic's performance against two established baseline approaches: Latent Dirichlet Allocation (LDA) and Latent Semantic Analysis (LSA). BERTopic significantly outperformed both baseline methods across all metrics:

Table 2: Comparative performance of BERTopic, LDA, and LSA on requirement analysis.

Model	Coherence	Homogeneity	Execution Time (min)	Hardware
BERTopic	0.74	0.67	7.8	CPU
BERTopic	0.72	0.64	6.8	GPU
BERTopic	0.709	0.63	6.5	TPU
LDA	0.52	0.42	3.2	CPU
LSA	0.48	0.38	2.1	CPU

The improved coherence translates directly to more interpretable and practically useful requirement clusters, as evidenced by the qualitative analysis of topic representations. These results confirm that transformer-based embeddings provide substantial advantages for requirements analysis compared to traditional statistical approaches, capturing the complex semantic relationships present in technical documentation more effectively.

6 Discussion

This section interprets our findings, analyzing the implications for requirements engineering practice and research. We discuss the meaning of identified topics, insights gained from BERTopic analysis, advantages over traditional methods, and improvements in semantic understanding.

6.1 Interpretation of Identified Requirement Topics

The hierarchical clustering visualization revealed clear separation between operational requirements and quality-oriented documents, demonstrating BERTopic's ability to differentiate functional and non-functional aspects without explicit training. This aligns with established software engineering frameworks that distinguish between what a system does (functional) and how well it does it (non-functional).

The natural clustering patterns closely correspond to recognized software engineering domains. For example, gaming-oriented requirements formed a distinct cluster, while security-focused elements created a separate protection-oriented category. This natural emergence of domain-specific clusters validates BERTopic's exceptional capability at comprehending specialized vocabulary and semantic associations, leveraging transformer architecture to process complex technical terminology in ways traditional vector space models are unable to achieve.

Functional requirement categories including database management and interface usability emerged organically within the model's output, confirming the algorithm's sophistication in generating meaningful taxonomies without requiring predefined classification systems. These results demonstrate substantial advancement over orthodox methods, especially in the engineering domain which requires semantic and coherent understanding of relationships between varied inputs.

6.2 Insights Gained Through BERTopic Analysis

BERTopic provides a comprehensive overview of how requirements naturally cluster themselves into groups, as visualized in the intertopic distance map. Densely packed clusters indicate strong semantic connections between requirements, while standalone topics denote unique requirement domains with minimal conceptual overlap with other areas.

Hierarchical relationships displayed in the dendrogram visualization reveal additional dependencies among requirements. Topics near each other in the dendrogram often represent requirements that, while classified differently, share underlying technical considerations. This visualization exposes potential cross-cutting concerns-requirements that impact multiple functional areas but might be documented in isolation.

These semantic connections enable several valuable capabilities for requirements engineering:

- **Identification of Undocumented Dependencies:** Topic proximity reveals potential dependencies between requirements that might not be explicitly documented in traditional specifications.
- **Discovery of Cross-cutting Concerns:** The model effectively identifies quality attributes (like security and performance) that span multiple functional domains, helping ensure consistent application of these concerns.

- **Impact Analysis:** Understanding the semantic connections between requirements enables more accurate assessment of how changes in one requirement might affect related areas.

6.3 Advantages Over Traditional Requirement Analysis Methods

The transformer-based approach demonstrated several significant advantages over traditional requirements analysis methods:

1) **Contextual Understanding:** Unlike keyword-based approaches that struggle with synonymy and polysemy, BERTopic effectively captures contextual meaning. For example, it correctly associates terms like "quick response" and "low latency" with performance requirements despite using different terminology.

2) **Scalability:** While manual analysis becomes increasingly impractical as requirements volume grows, our approach maintained consistent coherence scores across the dataset. The linear time complexity (with respect to document number) makes it suitable for large-scale systems with thousands of requirements.

3) **Consistency:** Manual requirements analysis often suffers from analyst subjectivity and fatigue. Our automated approach produced consistent results across multiple runs, providing a more reliable foundation for requirements engineering tasks.

4) **Discovery of Hidden Relationships:** The unsupervised nature of the approach revealed connections between requirements that might be missed in predetermined classification schemes, highlighting emergent patterns across organizational or documentation boundaries.

6.4 Semantic Understanding Improvements

BERTopic significantly enhanced semantic comprehension through several mechanisms:

- **Contextual Word Representation:** The transformer architecture distinguished between different uses of the same term-for example, understanding "user" differently in "user interface" versus "user authentication" contexts.

- **Technical Term Preservation:** The approach successfully maintained the integrity of multi-word technical terms like "anti-lock braking system" that carry specific meaning in requirements documentation.

- **Semantic Bridging:** The model effectively connected requirements using semantically similar but lexically different terminology-a critical capability for integrating requirements from diverse stakeholders.

- **Hierarchical Concept Recognition:** The clustering approach captured both high-level concepts and their specific implementations, reflecting the natural hierarchical structure of requirements.

The superior coherence score compared to traditional LDA and LSA quantifies these improvements, translating to more interpretable and actionable requirement groupings that better align with expert analysis.

These semantic understanding capabilities address key challenges in requirements engineering, particularly in large, complex systems where requirements come from multiple sources and evolve over time. By capturing the rich semantic relationships between requirements, BERTopic provides a foundation for more effective requirements management, traceability, and validation.

7 Practical Applications

This section explores concrete applications of BERTopic for requirements engineering tasks, demonstrating how the approach can be integrated into existing workflows to address common challenges.

7.1 Application to Requirement Classification

BERTopic can be seamlessly integrated into existing requirement management processes to facilitate automated classification. The unsupervised clustering approach reduces manual categorization workload by automatically identifying distinct requirement patterns based on semantic content rather than predefined labels.

The implementation workflow involves:

1) **Initial Clustering:** Running BERTopic on the requirement corpus to generate topic clusters.

2) **Label Assignment:** Mapping discovered topics to organizational requirement categories.

3) **Classification System:** Implementing a classification system that applies these mappings to new requirements.

This approach offers several advantages over traditional classification methods:

- **Adaptability:** The model naturally accommodates emerging requirement types that might not fit existing classification schemes.
- **Consistency:** Automated classification ensures uniform application of categories across large requirement sets.
- **Discovery:** The unsupervised approach may reveal meaningful subcategories within established requirement types.

In our case study, mapping the 52 discovered topics to the 14 ground-truth requirement categories achieved 76% classification accuracy without any supervised training, demonstrating the approach's effectiveness as a semi-automated classification tool.

7.2 Identification of Missing Requirements

The topic structure revealed by BERTopic provides a powerful framework for identifying potentially missing or underspecified requirements:

- **Gap Detection:** Sparse areas in the topic space highlight requirement domains that may be underdeveloped relative to system complexity.
- **Consistency Checking:** Comparing topic distributions against industry norms or similar projects can reveal domains requiring additional requirements.
- **Relationship Analysis:** The hierarchical clustering exposes dependencies that might suggest additional requirements to ensure complete coverage.

For example, the topic map revealed minimal coverage of localization requirements despite several identified internationalization topics, exposing a potential gap in the requirement set.

7.3 Detection of Inconsistencies and Overlaps

BERTopic's semantic analysis capabilities provide effective mechanisms for identifying potential requirement issues:

- **Contradiction Detection:** Requirements with high semantic similarity but conflicting specifications within the same topic cluster can be flagged for review.
- **Redundancy Identification:** Closely positioned topics with high term overlap often indicate potential redundancies.
- **Terminology Standardization:** Variations in terminology for similar concepts across requirements can be identified and harmonized.

When applied to our dataset, this approach identified 28 potential inconsistencies, of which 23 were confirmed as actual conflicts by domain experts, and also identified 45 redundant requirements, reducing documentation volume by approximately 5% while maintaining complete functional coverage.

7.4 Requirements Prioritization Framework

We developed a prioritization framework that leverages BERTopic's semantic understanding to inform requirement prioritization decisions:

- **Centrality Analysis:** Topics with high connectivity in the semantic map often represent core system functions that warrant higher priority.
- **Dependency Mapping:** The hierarchical clustering reveals implementation dependencies that suggest prioritization order (root topics before dependent ones).
- **Impact Assessment:** Requirements with connections to multiple topics have broader system impact and may deserve earlier attention.

When evaluated against expert prioritization decisions, this algorithm achieved 73% agreement with human judgments, significantly outperforming random prioritization and simple frequency-based approaches.

7.5 Traceability Enhancement

BERTopic significantly enhances requirement traceability through its semantic understanding:

- **Semantic Tracing:** The embedding similarity enables tracing between requirements and implementation artifacts based on semantic content rather than exact terminology.
- **Implicit Relationship Discovery:** The model reveals relationships between requirements that might not be explicitly linked in traditional documentation.
- **Bidirectional Mapping:** The approach supports both forward and backward traceability across the development lifecycle.

When evaluated against manually created traceability matrices, this approach achieved recall of 82% and precision of 76%, and identified previously undocumented trace links that were confirmed as valid by domain experts.

The practical applications demonstrate how BERTopic can be integrated into existing requirements engineering processes to address common challenges in classification, completeness, consistency, prioritization, and traceability, providing concrete solutions to persistent problems in the field.

8 Limitations and Future Work

This section critically examines the current limitations of our approach and outlines directions for future research to address these challenges and extend the capabilities of transformer-based topic modeling for requirements engineering.

8.1 Current Limitations

While our BERTopic implementation demonstrates significant potential for requirements analysis, several important limitations must be acknowledged:

- **Domain Vocabulary Limitations:** Although the transformer model effectively handles general software terminology, highly specialized domain vocabulary (e.g., specific financial regulations or medical device terminology) may not be adequately represented in the pre-trained embedding space. Experiments showed degraded performance (coherence scores dropping by approximately 15%) when analyzing requirements with highly specialized terminology.
- **Evaluation Scope:** Our evaluation relied primarily on quantitative coherence metrics and limited qualitative assessment. While these metrics provide valuable insights, they may not fully capture all aspects of practical utility for requirements engineering tasks. Broader evaluation involving diverse stakeholders and multiple projects would strengthen validity.
- **Static Analysis:** The current implementation provides a snapshot analysis of requirements at a single point in time, without specifically addressing the dynamic nature of requirements evolution. This limitation is particularly relevant in agile development environments where requirements frequently change and evolve.

- **Multimodal Limitations:** The text-only approach cannot analyze non-textual requirements artifacts such as diagrams, UML models, or visual specifications that often complement textual requirements. This creates a potential blind spot in comprehensive requirements analysis.
- **Scalability Constraints:** While our approach handled the dataset of 977 requirements efficiently, scalability to very large requirement sets (tens of thousands of items) remains to be thoroughly evaluated. Preliminary extrapolations suggest that processing time would increase linearly, but memory requirements might create bottlenecks for extremely large datasets.
- **Language Dependence:** The current implementation focuses on English-language requirements. Though transformer models support multilingual capabilities, we have not specifically evaluated performance for requirements documented in multiple languages.
- **Explanation Limitations:** While topic representations provide insights into cluster formation, the approach lacks comprehensive explainability mechanisms to help users understand why specific requirements were grouped together, potentially limiting trust and adoption.

8.2 Future Research Directions

Based on the identified limitations and promising results, we propose several directions for future research:

- **Multimodal Requirements Modeling:** Extending the approach to incorporate visual elements through multimodal transformers that can jointly analyze text and diagrams would provide more comprehensive requirements analysis.
- **Dynamic Topic Modeling:** Adapting the approach to support dynamic topic modeling would enable tracking requirement evolution throughout the project lifecycle, capturing how requirements change across development iterations.
- **Interactive Refinement:** Developing interactive interfaces that allow requirements engineers to adjust topic boundaries based on domain knowledge would combine the strengths of automated analysis with human expertise.
- **Transfer Learning for Specialized Domains:** Creating domain-adapted models that fine-tune transformer embeddings on specialized technical documentation would improve performance for highly technical domains.
- **Cross-Project Knowledge Transfer:** Leveraging models trained on previous projects to inform requirements analysis for new projects could enable valuable knowledge transfer and pattern recognition across the organization's project portfolio.
- **Industry Adoption Frameworks:** Developing comprehensive frameworks for integrating BERTopic into existing requirements engineering processes, including specialized plugins for popular requirements management tools, would accelerate practical adoption.

- **Requirements Quality Assessment:** Extending the approach to automatically evaluate requirement quality attributes (completeness, consistency, testability) based on semantic characteristics would provide additional value for requirements engineering teams.
- **Multilingual Requirements Analysis:** Evaluating and optimizing performance for multilingual requirements documentation would support global development teams working across language boundaries.
- **Explainable Topic Modeling:** Enhancing the explainability of topic assignments through attention visualization or feature attribution techniques would improve transparency and trust in automated recommendations.
- **Hierarchical Requirements Modeling:** Extending the approach to explicitly model hierarchical relationships between high-level and detailed requirements would better align with typical requirements organization structures.

These research directions address the identified limitations while building on the promising foundation established in this work. The continued evolution of transformer architectures and topic modeling techniques suggests significant potential for further improving automated requirements analysis in the coming years.

9 Conclusion

This paper has presented a comprehensive framework for applying transformer-based topic modeling to software requirements analysis, demonstrating how BERTopic can address persistent challenges in requirements engineering through enhanced semantic understanding.

Our evaluation, conducted on a diverse dataset of 977 software requirements across 14 categories, demonstrates that BERTopic significantly outperforms traditional approaches such as LDA and LSA, achieving a coherence score of 0.74 compared to 0.52 and 0.48, respectively. This quantitative improvement translates to more interpretable, practically useful requirement clusters that better align with software engineering conceptual frameworks.

The key contributions of this research include:

- **Methodological Framework:** We have developed and validated a systematic approach for applying transformer-based topic modeling to requirements analysis, including domain-specific preprocessing techniques, embedding model selection criteria, and evaluation metrics tailored to requirements engineering contexts.
- **Empirical Validation:** Our comprehensive evaluation demonstrates BERTopic's effectiveness for requirements analysis across multiple dimensions, including topic coherence, classification alignment, and practical utility for requirements engineering tasks.
- **Practical Applications:** We have identified and implemented specific applications of the approach to core requirements engineering challenges, including classification, gap analysis, inconsistency detection, prioritization, and traceability enhancement.

- **Limitation Analysis:** We have critically examined the current limitations of the approach and outlined a research agenda to address these challenges and extend capabilities for requirements engineering practice.

The results demonstrate that transformer-based topic modeling offers significant advantages for requirements analysis compared to traditional approaches. By capturing contextual relationships between technical terms, maintaining the integrity of multi-word concepts, and identifying semantic similarities despite terminological variations, BERTopic provides a powerful foundation for addressing the semantic precision, scale complexity, and evolution management challenges identified in the introduction.

The practical applications demonstrate how these theoretical advantages translate to concrete benefits for requirements engineering practice, enabling more efficient classification, improved completeness checking, enhanced consistency validation, informed prioritization, and enriched traceability. These capabilities directly address the core challenges that continue to plague requirements engineering in complex software projects.

While limitations remain, particularly around specialized domain vocabulary, dynamic requirements evolution, and multimodal analysis, the promising results suggest significant potential for further advancing requirements engineering through transformer-based approaches. The research directions outlined in this paper provide a roadmap for addressing these limitations and continuing to enhance automated support for requirements engineering.

As software systems continue to grow in complexity and requirements engineering remains a critical determinant of project success, approaches that enhance semantic understanding at scale will become increasingly essential. This research demonstrates that transformer-based topic modeling offers a promising path forward, combining the contextual understanding of modern NLP with the practical needs of software engineering.

References

[1] Karina Curcio, Tiago Navarro, Andreia Malucelli, Sheila Reinehr, "Requirements engineering: A systematic mapping study in agile software development," *Journal of Systems and Software*, vol. 139, pp. 32–50, 2018. doi: 10.1016/j.jss.2018.01.036

[2] J. Yang, Y. Dou, X. Xu, Y. Ma and Y. Tan, "A BERT and Topic Model Based Approach to reviews Requirements Analysis," in *Proc. 14th Int. Symp. on Computational Intelligence and Design (ISCID)*, Hangzhou, China, 2021, pp. 387–392. doi: 10.1109/ISCID52796.2021.00094

[3] H. H. Altarturi, K.-Y. Ng, M. I. H. Ninggal, A. S. A. Nazri and A. A. A. Ghani, "A requirement engineering model for big data software," in *Proc. IEEE Conf. on Big Data and Analytics (ICBDA)*, Kuching, 2017, pp. 111–117. doi: 10.1109/ICBDAA.2017.8284116

[4] Gunawardhana, L., "Process of Requirement Analysis Link to Software Development," *Journal of Software Engineering and Applications*, vol. 12, pp. 406–422, 2019. doi: 10.4236/jsea.2019.1210025

[5] de la Rosa, J., Pérez, Á., de Sisto, M. et al., "Transformers analyzing poetry: multilingual metrical pattern prediction with transformer-based language models," *Neural Comput & Applic*, vol. 35, pp. 18171–18176, 2023. doi: 10.1007/s00521-021-06692-2

[6] Bhukya, S.N., Pabboju, S., "Software engineering: risk features in requirement engineering," *Cluster Comput*, vol. 22 (Suppl 6), pp. 14789–14801, 2019. doi: 10.1007/s10586-018-2417-3

[7] S. T. Demirel and R. Das, "Software requirement analysis: Research challenges and technical approaches," in *Proc. 6th Int. Symp. on Digital Forensic and Security (ISDFS)*, Antalya, Turkey, 2018, pp. 1–6. doi: 10.1109/ISDFS.2018.8355322

[8] Chazette, L., Brunotte, W. & Speith, T., "Explainable software systems: from requirements analysis to system evaluation," *Requirements Eng*, vol. 27, pp. 457–487, 2022. doi: 10.1007/s00766-022-00393-5

[9] Lepri, B., Oliver, N., Letouzé, E. et al., "Fair, Transparent, and Accountable Algorithmic Decision-making Processes," *Philos. Technol.*, vol. 31, pp. 611–627, 2018. doi: 10.1007/s13347-017-0279-x

[10] Ambreen, T., Ikram, N., Usman, M. et al., "Empirical research in requirements engineering: trends and opportunities," *Requirements Eng*, vol. 23, pp. 63–95, 2018. doi: 10.1007/s00766-016-0258-2

[11] N. Niu and S. Easterbrook, "Extracting and Modeling Product Line Functional Requirements," in *Proc. 16th IEEE Int. Requirements Engineering Conf.*, Barcelona, Spain, 2008, pp. 155–164. doi: 10.1109/RE.2008.49

[12] L. Baresi, L. Pasquale and P. Spoletini, "Fuzzy Goals for Requirements-Driven Adaptation," in *Proc. 18th IEEE Int. Requirements Engineering Conf.*, Sydney, Australia, 2010, pp. 125–134. doi: 10.1109/RE.2010.25

[13] D. Ameller, C. Ayala, J. Cabot and X. Franch, "How do software architects consider non-functional requirements: An exploratory study," in *Proc. 20th IEEE Int. Requirements Engineering Conf. (RE)*, Chicago, IL, USA, 2012, pp. 41–50. doi: 10.1109/RE.2012.6345838

[14] M. Glinz, "On Non-Functional Requirements," in *Proc. 15th IEEE Int. Requirements Engineering Conf. (RE 2007)*, Delhi, India, 2007, pp. 21–26. doi: 10.1109/RE.2007.45