Natural Language Processing (NLP) for Requirements Engineering: A Systematic Mapping Study

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Context: NLP4RE – Natural language processing (NLP) supported requirements engineering (RE) – is an area of research and development that seeks to apply NLP techniques, tools and resources to a variety of requirements documents or artifacts to support a range of linguistic analysis tasks performed at various RE phases. Such tasks include detecting language issues, identifying key domain concepts and establishing traceability links between requirements. Objective: This article surveys the landscape of NLP4RE research to understand the state of the art and identify open problems. Method: The systematic mapping study approach is used to conduct this survey, which identified 404 relevant primary studies and reviewed them according to five research questions, cutting across five aspects of NLP4RE research, concerning the state of the literature, the state of empirical research, the research focus, the state of the practice, and the NLP technologies used. Results: (i) NLP4RE is an active and thriving research area in RE that has amassed a large number of publications and attracted widespread attention from diverse communities; (ii) most NLP4RE studies are solution proposals having only been evaluated using a laboratory experiment or an example application; (iii) most NLP4RE studies have focused on the analysis phase, with detection as their central linguistic analysis task and requirements specification as their commonly processed document type; (iv) 130 new tools have been proposed by the selected studies to support a range of linguistic analysis tasks, but there is little evidence of adoption in the long term, although some industrial applications have been published; (v) 140 NLP techniques (e.g., POS tagging and tokenization), 66 NLP tools (e.g., Stanford CoreNLP and GATE) and 25 NLP resources (WordNet and British National Corpus) are extracted from the selected studies, but most of them – particularly those novel NLP techniques and specialized tools – are not in frequent use; by contrast, frequently used NLP technologies are syntactic analysis techniques, general-purpose tools and generic language lexicons. Conclusion: There is a huge discrepancy between the state of the art and the state of the practice in current NLP4RE research, indicated by insufficient industrial validation of NLP4RE research, little evidence of industrial adoption of the proposed tools, the lack of shared RE-specific language resources, and the lack of NLP expertise in NLP4RE research to advise on the choice of NLP technologies.
1. Introduction

The important role of natural language (NL) in requirements engineering (RE) has long been established [1], [2]. In a survey published in 1981, aimed at providing an overview of techniques for expressing requirements and specifications, Abbott and Moorhead stated that “the best language for requirements is natural language [3].” While it is difficult to prove that NL is actually the best option, empirical evidence over the years has shown that it is at least the most common notation for expressing requirements in the industrial practice. The online survey of 151 software companies in the early 2000s by Mich et al. [4] concluded that in 95% percent of the cases requirements documents were expressed in some form of NL. This dominance of NL was confirmed by a recent survey of Kassab et al. [5], which involved 250 practitioners. The majority of the participants (61%) in that survey stated that NL was normally used in their companies for describing and specifying software and system requirements. Therefore, based on the past and current empirical evidence, we can safely assume that NL will continue to serve as the lingua franca for requirements in the future as well.

The close relationship between NL and requirements has been a source of inspiration for researchers to seek to apply natural language processing (NLP) techniques and tools to processing requirements texts [2]. Among the pioneering researchers are Chen [6] and Abbott [7], who, in the early 1980s, proposed using syntactic features of English sentences for database modeling and program design. These efforts were mostly based on extracting relevant entities from the requirements text based on simple syntactic rules, assuming that NL requirements were expressed in some constrained, predictable format, which, however, is not always the case in practice [8]. After these pioneering works, the beginning of 1990s saw some serious attempts to develop NLP tools for RE, introducing techniques to account for the complexity and variety of NL. Two well-known NLP tools, findphrases by Aguilera and Berry [9] and OICSI by Rolland and Proix [1], were the results of these efforts. While findphrases aimed to identify correlated words and phrases in a requirements text, OICSI intended to find concepts and relationships in the requirements, using lexical affinity and semantic cases [10], respectively.

For the remaining 1990s right up to the beginning of 2000s, a succession of NL tools had been proposed, among which were AbstFinder by Goldin and Berry [11], NL-OOPS by Mich [12], Circe by Ambriola and Gervasi [13], CM-Builder by Harmain and Gaizauskas [14], QuARS by Fabbri et al. [15], and ARM by Wilson et al. [16]. Most of the works in that period were oriented to identify relevant entities in the requirements, to possibly produce some form of abstract model, and to identify requirements quality defects. The early 2000s appears to be a period of experimentation with new NLP techniques and new ideas. This time witnessed the application of information retrieval (IR) techniques to requirements tracing [17], part-of-speech (POS) tagging to tagging related requirements sentences [18] and statistical NLP techniques to identifying “shallow knowledge” from requirements text [19] as well as to tracing relationships between requirements [20]. Since the late 2000s, NLP supported RE – NL4RE for short – has become a full-fledged research area [21], attracting researchers from the wider RE community. A large number of tools have since been developed, among which are SREE (Tjong and Berry [22]) for ambiguity detection and aToucan (Yue et al. [23]) for model generation. Recent developments include tools for requirements classification [24], detection of defects [25], smells [26] and equivalent requirements [27], glossary extraction [28], and requirements tracing [29].

With the recent widespread availability of NL content relevant to RE, such as feedback from users in app stores and social media, and developers’ comments in discussion forums and bug tracking systems, we have observed a rising interest in using NLP techniques, combined with big data analysis, to support data-driven RE [30] and crowd-based RE [31]. These emerging areas aim to leverage information available from stakeholders’ implicit and explicit feedback, to improve RE activities such as requirements elicitation and prioritization. Furthermore, given the increasing need to make software systems trustworthy, accountable, legally compliant, as well as security- and privacy-aware, and since most of the legally binding documents are expressed in NL, NLP has been largely applied also to legal documents [32] and privacy policies [33], in the field of RE and Law. Finally, to support Agile
software development, requirements expressed in the form of user stories have been identified as an interesting area of application for NLP [34].

As a witness of this great interest in NLP applications to RE problems, a dedicated venue has also been set up in the form of workshop, called NLP4RE [35] and co-located with the International Working Conference on Requirements Engineering: Foundations for Software Quality (REFSQ), in both 2018 and 2019. This indicates that not only the research field is growing, but also an active community is emerging in RE.

Some companies have also started to develop NLP tools for RE. For example, Qualicen GmbH\(^1\) developed Requirements Scout, a tool to analyze requirements specifications aiming to uncover requirements smells, i.e., defects; thingsThinking\(^2\) proposed Semantha, a tool to perform document comparison on a semantic level; QRA Corp\(^3\) includes QVscribe in its portfolio, a tool for quality and consistency checking; OSSENO Software GmbH\(^4\) developed ReqSuite, a tool to support requirements writing and analysis; and even IBM has recently developed IBM Engineering Requirements Quality Assistant\(^5\), a tool for automated requirements analysis and management that leverages the advanced NLP capabilities of IBM Watson\(^6\). This suggests that NLP4RE research is being transformed into a practical technology that can serve real world practice of RE.

However, in spite of its long history and this increasing interest, except for a small number of reviews that focus on specific topics of NLP4RE, there has been no effort to provide a comprehensive view of the field as a whole. We believe such an overview is crucial to the further development and success of the field, as it can play an important role in understanding the current state of NLP4RE research and identifying open problems. To this end, this article presents a first ever, large-scale systematic mapping study of NLP4RE research that we conducted in 2019. The mapping study reviewed 404 relevant primary studies reported between 1983 and April 2019, and structured them using a classification scheme to identify research trends and gaps. Five research questions were formulated to shape and steer the mapping study: What is the state of the literature on NLP4RE? What is the state of empirical research in NLP4RE? What is the focus of NLP4RE research? What is the state of the practice in NLP4RE? What are the enabling NLP technologies for NLP4RE research? The answers to these questions – that is, the results of the mapping study – are reported in this article.

To continue, Section 2 sets the scene by introducing the concepts of NLP and NLP4RE. Section 3 presents the related reviews to show the need for this mapping study. Section 4 describes the method for our mapping study while the mapping results are analyzed in Section 5. Section 6 reflects on the key findings and their implications for future research and practice. Section 7 discusses the validity threats to this mapping study and our countermeasures. Finally, Section 8 draws some conclusions based on the mapping study.

## 2. Concepts and Definitions

### 2.1 Natural Language Processing (NLP)

NLP is a field that employs computational techniques for the purpose of learning, understanding and producing human language content [36]. Liddy [37] provided this definition:

**Definition 1:** Natural Language Processing is a theoretically motivated range of computational techniques for analyzing and representing naturally occurring texts at one or more levels of linguistic analysis for the purpose of achieving human-like language processing for a range of tasks or applications [37].

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\(^1\) https://www.qualicen.de/en/
\(^2\) https://www.thingsthinking.net
\(^3\) https://qracorp.com
\(^4\) https://www.osseno.com/en/
\(^5\) https://www.ibm.com/us-en/marketplace/requirements-quality-assistant
\(^6\) https://www.ibm.com/watson
In this definition, the notion of “levels of linguistic analysis” refers to the phonetic, morphological, lexical, syntactic, semantic, discourse, and pragmatic analysis of language [37], the assumption of which is that humans normally utilize all of these levels to produce or comprehend language [38]. NLP systems may support different levels, or combinations of levels of linguistic analysis. The more levels of analysis NLP systems support, the stronger or more capable these systems are supposed to be. Today, apart from a few pioneering efforts on discourse and pragmatic processing, start-of-the-art NLP technologies have only reached the lexical and syntactic processing levels for full-fledged English, with limited semantic capabilities [39].

The approaches to NLP can be broadly classified into symbolic NLP and statistical NLP [37]. Although both types of NLP have been investigated at the same time since the early days of the NLP field (circa 1950s), until the 1980s, it was the symbolic NLP that dominated the field.

Symbolic NLP emerged from artificial intelligence (AI). It is based on explicit representation of facts about language and associated algorithms and uses this knowledge to perform deep analysis of linguistic phenomena [37]. Symbolic NLP approaches include logic or rule-based systems, and semantic networks. In rule-based systems, linguistic knowledge is represented as facts or production rules, whereas in semantic networks, this knowledge is represented as a network of interconnected concepts.

However, symbolic NLP approaches lack the flexibility to adapt dynamically to new language phenomena, because they use the handwritten rules or the explicit representations built by human analysis of well-formulated examples to analyze input text [37]. Such rules may become too numerous to manage [40]. In addition, symbolic approaches may be frail when presented with unfamiliar, or ungrammatical input [37]. Beginning in the 1980s, but more widely in the 1990s, statistical NLP had regained popularity, as a result of the availability of critical computational resources and ML methods [36]. Since then, statistical NLP has been the mainstream NLP research and development [39]. For example, many of today’s NLP tools such as POS taggers and syntactical parsers are based on statistical NLP [41].

In contrast to symbolic NLP, which uses detailed handwritten rules, statistical NLP employs various machine learning (ML) methods and large quantities of linguistic data (text corpora) to develop approximate, probabilistic models of language. These statistical models are simple and yet robust, because they are based on actual examples of linguistic phenomena provided by the text corpora, rather than deep analysis of linguistic phenomena as in symbolic NLP. When trained with large quantities of annotated language data, statistical NLP can produce good results, because it can learn most common cases in the copious data. Furthermore, the more abundant and representative the data, the better statistical NLP becomes.

However, statistical NLP can also degrade with unfamiliar or erroneous input [40], the problem similar to that of symbolic NLP. Furthermore, statistical NLP has been mainly useful for low-level NLP tasks such as lexical acquisition, parsing, POS tagging, collocations, and grammar learning [37]. Today, many text and sentiment classifiers of statistical NLP are still solely based on the use of the words of a text to ascertain the meaning of the text, rather than using structure and semantics of the sentences or discourses of the text. Also, most statistical models are trained with text corpora of everyday usage language, such as WSJ (Wall Street Journal) articles. Consequently statistical NLP can be unreliable for domain-specific text such as software requirements.

Most recently, circa 2012, deep learning (DL) methods began to emerge in the NLP scene [42]. The central idea of DL is that it allows a machine to be fed with a large amount of raw data and to automatically discover the representations or features needed for detection or classification [43]. Thus DL requires very little feature engineering by hand. Furthermore, the features learned by DL models are high-level, allowing for better generalization even over new, unseen data. By contrast, conventional ML techniques used in NLP are limited in their ability to process natural data in their raw form. This means that constructing a statistical NLP system requires careful engineering and considerable domain expertise to design a feature extractor that transforms the raw text into a suitable internal representation (i.e., feature vector), from which the ML subsystem, often a text classifier, can detect or classify patterns in the input. Both NLP and deep learning experts predict that NLP is an area in which deep learning could make a large impact over the next few years [36], [43]. Nonetheless, recent trends in deep learning based NLP show that coupling symbolic AI will be key for stepping forward in the path from NLP to natural language understanding [42]. This reaffirms the view that symbolic approaches and statistical approaches are complementary.

Our mapping study will focus on the application of NLP technologies to NLP4RE, regardless whether they are based on symbolic or statistical NLP.
2.2 Natural Language Processing for Requirements Engineering (NLP4RE)

Based on the definition of NLP (Definition 1), we define NLP4RE as follows:

**Definition 2:** Natural language processing supported requirements engineering (NLP4RE) is an area of research and development that seeks to apply NLP technologies (techniques, tools and resources) to a variety of requirements documents or artifacts to support a range of linguistic analysis tasks performed at various RE phases.

This definition has a number of key elements. First, we establish NLP4RE as an area of research and development that seeks to apply NLP technologies. This has to be the precondition for NLP4RE, because NLP4RE is motivated and enabled by NLP. We differentiate between three types of NLP technology: NLP technique, NLP tool and NLP resource. A NLP technique is a practical method, approach, process, or procedure for performing a particular NLP task, such as POS tagging, parsing or tokenizing. A NLP tool is a software system or a software library that supports one or more NLP techniques, such as Stanford CoreNLP\(^7\), NLTK\(^8\) or OpenNLP\(^9\). A NLP resource is a linguistic data resource for supporting NLP techniques or tools, which can be a language lexicon (i.e., dictionary) or a corpus (i.e., a collection of texts). Existing lexicons include WordNet\(^10\) and FrameNet\(^11\), whereas examples of corpus include British National Corpus\(^12\) and Brown Corpus\(^13\).

Second, NLP4RE deals with a variety of requirements documents or artifacts. Most of requirements documents are expected to be in NL. This is particularly so in early phase RE, in which requirements analysts may have to consult a wide variety of documents in order to develop an understanding of the problem domain. Such documents include interview scripts, legal documents, standards, and operational procedures \([19]\). More recently, online product reviews \([44]\) have been found useful for understanding the needs and wants of end users. Consequently, the types of input to NLP4RE are broad and diverse.

Third, while NLP strives for human-like language processing, to achieve human-like performance \([37]\), NLP4RE has a less ambitious goal, as its main objective is to assist requirements analysts in performing various linguistic analysis tasks \([45], [46]\) for different RE areas or phases. Such tasks include detecting language issues, identifying key domain concepts and establishing traceability links between requirements, etc. As highlighted by Berry et al. \([45]\), the goal of NLP4RE tools is not to replace the human analyst but to complement their work with those clerical or data intensive activities in which a computerized system can be more effective than a human.

We use this broad definition of NLP4RE to delineate the scope of our mapping study and to help identify relevant studies to NLP4RE.

3. Related Reviews

The RE literature counts several surveys with various degrees of relevance and quality, and covering some specific areas of interest. A recent survey of empirical RE research by Daneva et al. \([47]\) identified 7 mapping studies and 49 systematic reviews, but none of them addresses the whole research field of NLP4RE targeted by our work. In conducting the literature search for this mapping study, we identified 18 reviews relevant to NLP4RE. Here, we provide a brief overview of these reviews, to show why we need to conduct the mapping study and why it is timely to do so.

Among those 18 reviews, four of them focus on modeling activities in software engineering. In particular, Loniewski et al. \([48]\) present a survey of RE techniques in the context of model-driven development, including the cases where model transformation involved the requirements expressed in NL. Yue et al. \([49]\) provide a review of different techniques for transforming textual

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\(^7\) [https://nlp.stanford.edu/software/]
\(^8\) [https://www.nltk.org]
\(^9\) [https://opennlp.apache.org]
\(^10\) [https://wordnet.princeton.edu/]
\(^11\) [https://framenet.icsi.berkeley.edu/fndrupal/]
\(^12\) [http://clu.uni.no/icame/manuals/]
\(^13\) [http://www.natcorp.ox.ac.uk/]

requirements into analysis models. In their review, NLP support for model transformation is also considered. On the other hand, the review presented by Nicolás and Toval [50] focuses on the techniques used to generate NL or formal requirements from models. The review by Dermeval et al. [51] covers the studies that use ontologies for requirements modeling and shows that most of the reviewed studies dealt with textual requirements by means of artificial intelligence techniques, including NLP, to support different language analysis tasks.

Another group of reviews is concerned with topics related to requirements management, including retrieval, tracing and classification of requirements. Specifically, Irshad et al. [52] reviewed the papers on requirements reuse, including the work that applied NLP and IR techniques to text similarity evaluation to match input queries with existing requirements in a repository. Torkar et al. [53] reviewed the different methodologies to support traceability, considering also approaches that use some textual analysis support. On a different note, but still related to requirements management, Binkhonain and Zhao [54] reviewed research on applying ML and NLP techniques to the classification of non-functional requirements. More oriented towards software product line engineering, Bakar et al. [55] surveyed the usage of NLP techniques in the identification of common and variant features in NL requirements documents as well as other NL sources, such as NL product descriptions. Building on this survey, Li et al. [56] focused on identifying features and analyzing their relationships in textual requirements.

A rather recent, yet lively, group of reviews is concerned with analysis of publicly available feedback produced by users and developers. Among these reviews, Martin et al. [57] reported a mapping study of the research on app store analysis in software engineering and identified NLP as relevant tools for feature analysis and app review analysis. Within the field of app review analysis, Tavakoli et al. [58] reviewed the application of ML and NLP techniques to extracting and classifying useful information from users’ feedback, so as to distinguish between requirements-relevant information and other types of users’ comments. Two recent reviews by Santos et al. [59], [60] were concerned with classification of app reviews and users’ feedback. Finally, with a broader focus on developers’ feedback, Nazar et al. [61] reviewed works on summarization of the various data sources, including bug reports, mailing lists and developer forums, to extract requirements related information.

Other reviews related to ours, but more limited in scope and extension, are those by: Ahsan et al. [62], on test generation from requirements; Shah et al. [63] on ambiguity detection in requirement also by means of NLP; Casamayor et al. [64], presenting a non-systematic survey on text mining and NLP in the field of model-driven design; and Nazir et al. [65], pursuing a mapping study on NLP for RE analogous to ours, but considering only 27 primary studies. Recently, an MSc Thesis reported on a systematic literature review on using NLP for requirements elicitation and analysis [66]. Although very rigorous, the review is limited to both its scope, as it only focused on requirements elicitation and analysis, and the number of studies included, as it surveyed 144 studies.

On the one hand, this vast landscape of recent reviews touching the field of NLP4RE shows that specific sub-fields have attracted increasing interest in the last years, raising the need for secondary studies to scope and guide the research in these areas. On the other hand, while specific NLP4RE topics are addressed, none of the existing reviews provides a comprehensive mapping study on NLP4RE, therefore making the current work particularly timely and useful to better conceptualize and identify potential synergies among the different areas of investigation, and establish novel research direction in this growing research field.

4. Review Method
To achieve our goal, we have carried out a systematic mapping study [67] using the basic method presented in [68]. This section presents our research questions and describes the main activities involved in the mapping study; we report our mapping results in Section 5.

4.1 Research Questions
The research questions (RQs) for our mapping study are stated as follows:

RQ1: What is the state of the literature on NLP4RE? Specifically, what is the population of the published literature on NLP4RE? What is the publication timeline? What are the leading publication venues?

RQ2: What is the state of empirical research in NLP4RE? Specifically, what types of research have been carried out in the area of
NLP4RE? What types of evaluation method have been used in the research? What relationships can be observed between these research types and evaluation methods?

**RQ3:** *What is the focus of the NLP4RE research?* Specifically, what RE phases have been addressed? What linguistic analysis tasks have been investigated for these phases? What is the relationship between these RE phases and tasks? What types of input document have been considered?

**RQ4:** *What is the state of the practice in NLP4RE?* Specifically, what new tools have been developed? Which RE phases and tasks do these tools support? Which of these tools are available to the public?

**RQ5:** *What are the enabling NLP technologies for the NLP4RE research?* Specifically, what NLP techniques, tools and resources have been employed? Which ones are most popular? What relationships can be observed between NLP technologies and NLP4RE tasks?

These five main RQs are interrelated, designed to interrogate the NLP4RE literature progressively, from the state of the literature (RQ1), to the state of empirical research reported in this literature (RQ2), to the focus of the NLP4RE research (RQ3), to the state of the practice in the NLP4RE area (RQ4), and finally, to the NLP technologies that enable NLP4RE research and practice (RQ5). Collectively, these RQs define the scope of our mapping study and articulate what we want to accomplish by doing this study. Each RQ is further elaborated into a set of specific questions, allowing us to survey the NLP4RE literature in great detail. Consequently, the answers to these specific questions collectively provide the answers to the five main RQs.

### 4.2 Study Selection Process

#### 4.2.1 Determining the Digital Libraries

We have identified the following digital libraries as the data sources for our mapping study: ACM Digital Library (ACM); IEEE Xplore Digital Library (Xplore); ScienceDirect (SD); SpringerLink (SL). These libraries were chosen because they host the major journals and conference proceedings related to software engineering (SE) and RE. To complement these libraries, we have also selected Association for Computational Linguistics Library (ACL), where the major contributions to NLP are likely to be published. These five libraries serve as our data sources for identifying the relevant literature.

#### 4.2.2 Formulating the Search Strategy

Our search strategy was based on the direct search of the electronic databases of the aforementioned five digital libraries. The search terms for querying these libraries were constructed using the steps presented in [69]. Specifically, we used the major terms “requirements engineering” (representing the context of the research) and “natural language processing” (representing the intervention in this context) as the base terms; elaborate each base term with alternative spellings and synonyms; use the Boolean OR to incorporate synonyms, alternative spellings, alternative terms, and sub-field terms into each base term set, and Boolean AND to link the two sets of terms. Several iterations were performed to identify and refine the keywords. The complete set of the search terms is presented in Table 1.

| Main Keywords               | Derived Keywords                                                                 |
|-----------------------------|----------------------------------------------------------------------------------|
| Requirements engineering    | Requirements elicitation, requirements analysis, requirements specification, requirements modeling, requirements validation, requirements verification, requirements management, requirements traceability, requirements classification, requirements document, requirements specification |
| Natural language processing | NLP, statistical NLP, machine learning, deep learning, information extraction, information retrieval, text mining, text analysis, linguistic instruments, linguistic approaches |

#### 4.2.3 Performing the Literature Search

The library search was completed in April 2019 and the results were downloaded and imported into an Endnote library where all duplicates were automatically removed by Endnote. Multiple pilot studies were performed to adjust the string and the categories before the final search. For the first four libraries, no publication timeline was specified in the queries; however, the search of ACL...
was restricted to the last 10 years, as NLP4RE research has only established itself as a subfield in RE in the recent years and we wanted to check whether it had some recent impact also on the NLP community. By default, only the publications written in English were retrieved from all libraries except SL and ACL, for which we explicitly set the language to English. The final results from the main search were 11,406. These results were then combined with the initial search results. Endnote automatically removed the duplicates and the remaining combined results are 11,489. Finally, we conducted a complementary search on Google Scholar, to check for additional studies not included in the main search results. This search retrieved 51 studies. Adding them to the search results in our Endnote library gave us a total of 11,540 items for study selection.

4.2.4 Selecting the Relevant Studies

We defined a set of inclusion and exclusion criteria to guide us in study selection. These criteria are shown in Table 2. Our criteria explicitly exclude the short papers, because in general such papers lack detailed description of their contributions and including them can potentially skew the results of the mapping study.

**Table 2: Inclusion (I) and Exclusion (E) Criteria for Selecting Relevant Studies**

| I/E | No. | Criteria |
|-----|-----|----------|
| I   | 1   | Include peer-reviewed primary studies that are relevant to NLP4RE (cross-checking and validation needed for such studies). |
| I   | 2   | If there are multiple relevant studies that report the same research, include the longest study only and exclude the rest of them. |
| E   | 1   | Exclude tables of contents, editorials, white papers, commentaries, extended abstracts, communications, books, tutorials, non-peer-reviewed papers, and duplicate papers. |
| E   | 2   | Exclude short papers that have fewer than 6 pages if they are in a single column format. |
| E   | 3   | Exclude reviews or secondary studies. |
| E   | 4   | Exclude papers that are clearly not relevant to NLP4RE (cross-checking and validation needed for such papers). |

Based on these criteria, a team of four data inspectors (Alhoshan, Letsholo, Ajagbe, Chioasca) and three supervisors (Zhao, Ferrari, Batista-Navarro) carried out study selection. The study selection process, depicted in Figure 1, is as follows.

**Figure 1: Study selection process.**

The inspectors initially applied E1 and E2 (Table 2) to the Endnote library, to remove irrelevant contents such as editorials, commentaries and so on. They also performed a series of checks to ensure no identical papers remained in the library. After this filtering, there were 6,324 papers left in the process. In the next step, the inspectors checked the length, title, abstract, introduction, and conclusion of each study, and removed short papers, irrelevant papers and secondary studies in accordance with E3 and E4. This step was autonomously performed by the inspectors, with the support of the lead supervisor (Zhao) for undecided cases.

The remaining 1,012 primary studies were divided between the four data inspectors, who independently reviewed their allocated studies according to I1 and I2 to determine if each of these studies should be included or excluded. This involved carefully reading the full text of each study to establish its relevance and to identify its key components with respect to our predefined categories. During the selection, the supervisors performed regular and random checking on the selected and deselected studies to ensure they were correctly included or excluded. Any discrepancies and inconsistencies were identified and immediately notified to the
responsible inspectors. After individual selection, the inspectors crosschecked each other’s results. Undecided cases were resolved with the involvement of all three supervisors. The selected studies by individual inspectors were then combined, resulting in a total of 416 studies. The lead supervisor carried out the final check on these 416 studies, by examining the title and abstract of each study, and in undecided cases, by reading the text of the study. This identified 4 duplicate studies and 8 irrelevant studies. The remaining 404 studies were included in our mapping study. The references of these studies are given in Appendix 1.

4.3 Data Extraction and Classification

4.3.1 Defining the Classification Scheme

Building a classification scheme is the central task of any mapping study, as the main purpose of a mapping study is to classify the literature [68], [70]. Our classification scheme reflects the five research questions. It is made up of four facets, each containing a set of categories. Figure 2 depicts this classification scheme, where the number associated with each category is the number of occurrences in that category, to be discussed in Section 5. The four facets and their categories are described as follows.

1. **Publication Facet.** This facet is for classifying the publication information. The resulting classification will be used to answer RQ1. This facet contains the following three categories: Publication Types, Publication Venues and Publication Years.

2. **Research Facet.** This facet is for classifying the selected studies according to their research types and evaluation methods. The resulting classification will be used to answer RQ2. This facet contains the following two categories:
   - **Research Types.** Five types of research are considered, using the taxonomy of Wieringa et al. [71] (see Table 3).
   - **Evaluation Methods.** Nine types of evaluation methods are considered, according to Chen and Babar [72] (see Table 4).

![Figure 2: Faceted classification scheme for mapping the NLP4RE literature.](image-url)
3. **Focus Facet.** This facet is for classifying the selected studies according to their RE phases, NLP4RE tasks and input documents. The resulting classification will be used to answer RQ3. This facet contains the following three categories:

- **RE Phases.** The RE phases are defined in Table 5, where “Other” is a placeholder, which can be replaced by Testing or Design, or other phases of the software process. The first five RE phases are based on the work of Cheng and Atlee [73].
- **NLP4RE Tasks.** NLP4RE tasks are linguistic analysis tasks performed during RE process. We use six general types of NLP4RE task for our mapping study, as shown in Table 6. The first four tasks are based roughly on the work of Berry et al. [45], whereas the last two are defined by us.
- **Input Document Types.** The selected studies are classified into categories according to the input document type they use. The document types used in this classification have not been predefined; they will be synthesized from the extracted data.

4. **Contribution Facet.** This facet is for classifying the contribution and the underlying technologies of the selected studies. The resulting classification will be used to answer RQ4 and RQ5. This facet contains the following two categories:

- **NLP4RE Tools.** These tools are the results reported by the NLP4RE literature.
- **NLP Technologies.** NLP technologies used by the selected studies are classified into three types: NLP Technique, NLP Tool and NLP Resource.

**Table 3: Types of Research for Classifying the NLP4RE Literature (Adapted from Wieringa et al. [71])**

| Research Type       | Explanation                                                                 |
|---------------------|-----------------------------------------------------------------------------|
| Evaluation Research | This type of research involves empirical evaluation from industries, often in the form of case study or field study. |
| Validation Research | This type of research does not involve new technologies; instead, it is concerned with validating existing technologies (methods, tools, algorithms etc.). Comparative studies are typically validation research. |
| Solution Proposal   | This type of research typically involves the development of a novel solution (e.g., a new method, technique or tool) to a problem. This type of research may contain validation research. |
| Philosophical/ Opinion | This type of research covers a broad range of work, under the guise of vision statements, position papers, opinions, viewpoints etc. This type of research is conceptual or theoretical, so its outcome is often a new understanding or a new perspective of some research area. |
| Personal Experience | This type of research is reflectional, based on personal experience of applying an existing technology to a real-world problem. |

**Table 4: Types of Evaluation Method for Classifying the NLP4RE Literature (based on Chen and Babar [72])**

| Evaluation Method                   | Explanation                                                                 |
|-------------------------------------|-----------------------------------------------------------------------------|
| Rigorous Analysis                   | Rigorous derivation and proof, suited for formal model.                     |
| Case Study                          | An empirical inquiry that investigates a contemporary phenomenon within its real-life context; when the boundaries between phenomenon and context are not clearly evident; and in which multiple sources of evidence are used. |
| Discussion                          | Provided some qualitative, textual, opinion.                               |
| Example                             | Authors describing an application and provide an example to assist in the description, but the example is “used to validate” or “evaluate” as far as the authors suggest. |
| Experience Report                   | The result has been used on real examples, but not in the form of case studies or controlled experiments, the evidence of its use is collected informally or formally. |
| Field Experiment                    | Controlled experiment performed in industry settings.                      |
| Laboratory Experiment with Human Subjects (LEHS) | Identification of precise relationships between variables in a designed controlled environment using human subjects and quantitative techniques. |
| Laboratory Experiment with Software Subjects (LESS) | A laboratory experiment to compare the performance of newly proposed system with other existing systems. |
| Simulation                          | Execution of a system with artificial data, using a model of the real word. |
Table 5: RE Phases for Classifying the NLP4RE Literature (Based on Cheng and Atlee [73])

| RE Phase               | Explanation                                                                                                                                                                                                 |
|------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Elicitation            | This phase comprises activities that enable the understanding of the goals, objectives, and motives for building a proposed software system.                                                                       |
| Analysis               | This phase involves evaluating the quality of recorded requirements and identifying anomalies in requirements such as ambiguity, inconsistency and incompleteness.                                               |
| Modeling               | This phase involves building conceptual models of requirements that are amenable to interpretation.                                                                                                           |
| Validation & Verification (V&V) | Requirements validation ensures that models and documentation accurately express the stakeholders' needs. Validation usually requires stakeholders to be directly involved in reviewing the requirements artifacts. Verification entails proving that the software specification meets these requirements. Such proofs often take the form of checking that a specification model satisfies some constraint (model checking). |
| Management             | This is an umbrella activity that comprises a number of tasks related to the management of requirements, including the evolution of requirements over time and across product families, and the task of identifying and documenting traceability links among requirements artifacts and between requirements and downstream artifacts. |
| Other                  | This is an open-end category that allows us to record other NLP4RE related software development activities. For example, during software testing, NLP may be used to analyze requirements to generate test cases. In this case “Other” will be replaced by “Testing”. During software design, NLP may be used to transform requirements into design artifacts. “Other” will be replaced by “Design”. |

Table 6: NLP4RE Tasks for Classifying the NLP4RE Literature

| NLP4RE Task       | Meaning                                                                 | Explanation                                                                                                                                                                                                 |
|-------------------|------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Detection         | Detect linguistic issues in requirements documents                     | This task is typically to support manual review activities to make the requirements, or requirements-related artifacts, clear and unequivocal. The linguistic issues to be detected may range from the controversial usage of passive voice, to the occurrence of typically vague phrases (e.g., as soon as possible, after some time) or weak verbs (e.g., may, could), to the presence of syntactic and pragmatic ambiguities. Also checking the adherence to pre-defined requirements templates, and identifying equivalent requirements, can be included in this task, as the goal is still to enforce rigor in requirements texts. |
| Extraction        | Identify key domain abstractions and concepts                           | This task normally aims to extract single or multi-word terms from requirements texts to establish domain-specific and project-specific glossaries, as requirements often include domain-specific, compound terms that are not commonly used. The extracted glossaries can be exploited for other objectives, including completeness or consistency checking, product comparison, classification, and modeling. |
| Classification     | Classify requirements into different categories                         | This task aims to classify requirements into different types, base on the purpose for which the task is applied. For example, requirements can be categorized based on their functional category, to ease requirements apportionment and reuse or based on its quality category, to identify non-functional requirements that may be hidden within functional ones. Also, when applied to users’ feedback and online discussions, classification can help identifying feedback that is specifically concerned with new requirements, or feedback referring to specific features of interest, possibly with the sentiment expressed by the product’s users. |
| Modeling          | Identify modeling concepts and constructing conceptual models           | The task typically makes use of the extraction task, and can take different flavors, from the generation of UML models to support analysis and design, to the synthesis of feature models in a product-line engineering context, to the generation of high-level models of early requirements or user stories to support project scoping. |
| Tracing & Relating | Establish traceability links or relationships between requirements, or between requirements and other software artifacts such as models, code, test cases, and regulations | This task mainly aims to support manual tracing activities oriented to enforce and demonstrate process consistency, especially in a regulated context or in large-scale enterprise software. We include in this class also those works dealing with change impact analysis, as they also address the problem of identifying relationships between requirements or other artifacts. |
| Search & Retrieval | Search and retrieve requirements or requirements sets from existing repositories | The goal of this task can be to reuse existing requirements assets to match with the needs of novel customers, or to support domain scoping towards the development of new product, by recommending specific features based on existing software descriptions available online. |
4.3.2 Extracting and Aggregating the Data

Our data extraction process was organized into four separate phases, described as follows. In Phase 1, we extracted the data for the categories and subcategories of the publication facet. These data were automatically obtained from our Endnote library where the selected studies were stored.

Phase 2 involved extracting the data for the categories and subcategories of the remaining three facets. To do so we first created a data extraction form on Google Sheets. The categories of the three facets (research, focus and contribution) were mapped onto the columns in the form. Some categories, i.e., RE phases and NLP4RE tasks, were given extra columns, to allow additional RE phases or tasks to be recorded. The rows of the form were used to record the data related to the selected studies, one row per study, and each row was identified by Study ID of a study. Next, we divided the selected studies evenly among the four data inspectors, who reviewed each study and performed data extraction for each study.

In parallel with the inspectors, the supervisors performed data extraction on the randomly selected studies and then compared the results with those obtained by the inspectors. Any discrepancy and inconsistency were discussed with the inspectors and actions taken to ensure the accuracy and consistency of the extracted data across the board.

After the completion of data extraction, in Phase 3, we carried out thematic synthesis on the descriptions related to input document types to identify specific input document types. We also performed thematic synthesis on the descriptions related to NLP techniques, NLP tools and NLP resources to create a coherent set of names for these technologies. The steps recommended by Cruzes and Dybå [74] were adopted for our thematic synthesis: code each piece of text with a label or term; translate related codes into the themes; organize the themes into high-level themes.

Finally, in Phase 4, we carried out data cleaning for each category to harmonize and standardize the terms in it; we inspected the members in each category to ensure our classification was accurate and consistent; we conducted statistical analysis of the categories; we employed a variety of visual tools [75], including tables, bar charts and dendrograms, to produce the visual representations of the analysis results [75], [76]. In the next section, we answer our five RQs based on the mapping results.

5. Mapping Results

5.1 RQ1: State of NLP4RE Literature

*Population of the NLP4RE literature.* A total of 404 primary studies relevant to NLP4RE have been identified by our mapping study, comprising 26.75% (108) journal articles, 58.17% (235) conference papers and 15.10% (61) workshop papers. Such a trend, as we observed, is consistent with other areas in RE [77] and SE [78].

*Publication timeline.* These studies have been published over the past 36 years, from 1983 to 2019 as Figure 3 shows (NB. The number of studies published in 2019 is incomplete, as our library search ended in April 2019); however, the majority of these studies (88.61% or 358 out of 404) have actually been published since 2004. This means that before 2004, an average publication rate was roughly two papers per year, whereas after 2004 it was about 24 papers per year. This rapid growth can be attributed to technological advances in NLP over the past 15 years or so [36].

*Publication venues.* These studies were found from 170 different publication venues (see Appendix 2). Of these, 12 venues are identified as the leading venues for these studies (see Figure 4), as they have collectively published 45.05% (or 182) of the selected studies. Thus, on average, each of these 12 venues has published 15.17 papers, whereas each of the remaining 158 venues has only published 1.41 papers. Although this extensive number of diverse venues indicates that NLP4RE is a topic of general interest – though not necessarily central – to diverse communities, such a wide spread of the venues also has its downside, as it makes locating relevant NLP4RE work and building a consolidated NLP4RE knowledge base a difficult task.

These 12 leading venues count some top RE and SE conferences and journals, as Figure 4 shows. It can be observed that the three top RE venues (RE, REFSQ and REJ) have published a quarter of all selected studies, indicating that these are the core publication channels for NLP4RE research. As it can also be observed from Figure 4, the five top SE conferences and journals (JSS, ASE, ICSE, IST, and TSE) have published more than a 10 percent of the studies, indicating that NLP4RE research has a broad audience
in the SE community. To assess the impact of NLP4RE research in the SE community, we compared the proportion of the NLP4RE papers published at ICSE with the proportion of the GORE (Goal-Oriented Requirements Engineering) papers published at ICSE [77]. We found that NLP4RE has produced 9/404 (2.25%) ICSE papers, whereas GORE has produced 5/246 (2.03%), indicating that NLP4RE has made a similar impact on SE as CORE. Given that GORE is a well-established subfield in RE with a long research tradition, these comparable results show that NLP4RE has now become an important research area in RE, with relevant impact outside the RE field.

![Figure 3: Publication timeline of the 404 selected studies.](image)

Although the ACL library was included in our library search, we only found two relevant studies from it. The reason might be that the main publication venues for NLP4RE still focus on RE and SE, and that the interest of the NLP community in RE-related studies is still limited. As NLP represents one crucial facet of NLP4RE, engagement with the NLP research community is important for NLP4RE researchers. One way of doing this is to take NLP4RE research results to NLP conferences or journals for validation and feedback.

![Figure 4: Leading publication venues for NLP4RE research.](image)

### 5.2 RQ2: State of Empirical Research in NLP4RE

To understand the state of the empirical research in NLP4RE, we analyze the types of research reported in the 404 studies, the evaluation methods used to validate these studies and the relationships between them. Figure 5 shows the distribution of the
selected studies among different research types, while Figure 6 depicts the distribution of the selected studies among different evaluation methods.

**Types of NLP4RE research.** Figure 5 shows that Solution Proposal is the most frequently used research type among the NLP4RE studies (67.08%). Validation Research is in a distant second, only on 17.33% studies. The remaining research types are less frequently used, ranked as follows: Evaluation Research (7.18%), Philosophical & Opinion (4.70%) and Personal Experience (3.71%). Such a trend was also reported in systematic reviews on other RE and SE areas [77], [78].

**Types of evaluation method for NLP4RE research.** From Figure 6, it is evident that Laboratory Experiment with Software Subjects (LESS) is the most frequently used evaluation method, followed by Example Application and Laboratory Experiment with Human Subjects (LEHS). Other evaluation methods are used less. In particular, Case Study, Discussion and Experience Report are only used by a small number of studies, while Field Experiment, Rigorous Analysis and Simulation are rarely used.

**State of empirical research in NLP4RE.** Empirical Research is the research that uses empirical evidence. Based on the types of empirical method used in SE [79], for the identified evaluation methods used for NLP4RE research, only LESS, LEHS, Case Study, and Field Experiment are counted as empirical methods, whereas the remaining methods are not. These four empirical methods form an experimental path that starts with laboratory experiments (LESS or LEHS) and ends with real-world validation using Case Study or Field Experiment [80]. While LESS and LEHS are conducted in a very controlled environment with simplified reality, Case Study and Field Experiment are performed in a less controlled and real environment. As more than 60% (243) studies are evaluated by a laboratory experiment (LESS or LEHS) as opposed to 7% by a Case Study or Field Experiment, Empirical Research in NLP4RE is still at the early stage of the experimental path, waiting to be evaluated rigorously by industrial case studies or field experiments.

**Relationships between NLP4RE research types and evaluation methods.** We now examine the relationships between the research types and the evaluation methods found in the selected studies. Using the pivot table (Table 7), we can observe an alignment between the research types and the evaluation methods applied. This alignment suggests that the selected studies have used appropriate evaluation methods for research validation. A further insight from Table 7 is that the typical NLP4RE study is a solution proposal, possibly evaluated through an experiment or example application, but without an evaluation in an actual industrial context.
5.3 RQ3: Focus of NLP4RE Research

To address this research question, we exclude personal experience and philosophical & opinion papers, because they do not provide data pertinent to this question. We are therefore left with 370 studies for RQ3. These studies consist of 271 solution proposals, 70 validation research studies and 29 evaluation research studies.

Most targeted and least targeted RE phases. Figure 7 shows the distribution of the 370 studies by the RE phases. Clearly, Analysis is by far the most targeted RE phase, followed by Management, Elicitation and Modeling. V&V (validation & verification), Testing and Design are the least targeted phases. Analysis as the most targeted phase by NLP4RE research may be due to its broad role in RE. The lack of attention to V&V may be because V&V is a phase at the boundary between requirements and the rest of the process. The same can be said to Testing and Design phases. This shows that the main focus of NLP4RE is the phases within the RE process, with limited attention to the relationship with the whole software process. This indicates an additional space for further research.

Table 7: Relationships between Research Types and Evaluation Methods

|                         | Solution Proposal | Validation Research | Evaluation Research | Philosophical & Opinion | Personal Experience | Row Total |
|-------------------------|-------------------|---------------------|---------------------|-------------------------|---------------------|------------|
| LESS                    | 140               | 37                  | 0                   | 0                       | 0                   | 177        |
| Example Application     | 94                | 0                   | 0                   | 0                       | 0                   | 94         |
| LEHS                    | 35                | 31                  | 0                   | 0                       | 0                   | 66         |
| Discussion              | 0                 | 0                   | 0                   | 19                      | 0                   | 19         |
| Case Study              | 0                 | 0                   | 25                  | 0                       | 0                   | 25         |
| Experience Report       | 0                 | 0                   | 0                   | 0                       | 15                  | 15         |
| Field Experiment        | 0                 | 0                   | 4                   | 0                       | 0                   | 4          |
| Rigorous Analysis       | 0                 | 2                   | 0                   | 0                       | 0                   | 2          |
| Simulation              | 2                 | 0                   | 0                   | 0                       | 0                   | 2          |
| **Column Total**        | **271**           | **70**              | **29**              | **19**                  | **15**              | **404**    |

Note that about a third of the studies have considered two separate RE phases in their research, but the investigation of the second phase was often brief and secondary. In order to not skew the statistics, we decided to focus only on the main RE phase targeted by each study.

Most studied and least studied NLP4RE tasks. Figure 8 shows the distribution of the 370 studies by the NLP4RE tasks. Evidently, Detection, Classification, Extraction, Modeling, and Tracing & Relating are the most studied tasks, whereas Search & Retrieval is the least studied task. In what follows, we identify the focus of NLP4RE research through the relationships between these tasks and the RE phases where these tasks are performed.

Relationships between NLP4RE tasks and RE phases. For each RE phase, we count the number of studies that investigate each NLP4RE task. The results are presented in Table 8 and briefly explained as follows:

- Analysis phase: The NLP4RE tasks investigated for this phase are broad, including Detection, Classification, Extraction, Tracing & Relating, and Search & Retrieval. This suggests that there are a variety of activities on this phase that can be supported by NLP techniques. This also shows why Analysis is the most targeted phase. Table 8 shows that Detection is the central task for this phase, suggesting that the main role of NLP in the Analysis phase is to help detect language issues in requirements documents.
- Management phase: The NLP4RE tasks investigated for this phase are also Detection, Classification, Extraction, Tracing & Relating, and Search & Retrieval, suggesting that there are a variety of activities on this phase that can be supported by NLP techniques. The central task on this phase is Tracing & Relating, indicating that the main role of NLP in this phase is to help identify traceability relationships between requirements.
- Elicitation phase: The NLP4RE tasks investigated for this phase are also Detection, Classification, Extraction, Tracing & Relating, and Search & Retrieval, suggesting that there are a variety of activities on this phase that can be supported by NLP techniques. The central task on this phase is extraction, indicating that the main role of NLP in this phase is to help extract requirements concepts.

- Modeling phase: In contrast to the aforementioned RE phases, the NLP4RE tasks investigated for this phase are much narrower, including only Extraction and Modeling. Clearly, the studies investigating the Modeling task have outnumbered the studies investigating the Extraction task, making Modeling the central task for this phase.

- V&V and Testing phases: The NLP4RE tasks investigated for these phases are the same, comprising Detection, Classification, Extraction, and Tracing & Relating. While this suggests that there are a variety of activities on these phases that can be supported by NLP techniques, from Table 8, it is difficult to deduce which of these tasks is central on these phases.

- Design phase: The NLP4RE tasks investigated for this phase are exactly the same as those for the Modeling phase. This suggests that the main role of NLP in this phase is also to help identify requirements concepts and relationships.

As it can be observed from Table 8, Analysis, Management, Elicitation, and Modeling are the focus of NLP4RE research, and each of these phases has a central or typical NLP4RE task that represents the main role of NLP in that phase. Though not a central task for any RE phase, Classification has received more attention than Tracing & Relating, which is a central task for Management, perhaps due to its importance and general applicability in RE.

As it can be observed from Table 8, Analysis, Management, Elicitation, and Modeling are the focus of NLP4RE research, and each of these phases has a central or typical NLP4RE task that represents the main role of NLP in that phase. Though not a central task for any RE phase, Classification has received more attention than Tracing & Relating, which is a central task for Management, perhaps due to its importance and general applicability in RE.
Types of input document processed by NLP4RE studies. From the identified input documents, we synthesized them into 14 different types, as Figure 9 shows. As the description of input documents in our reviewed studies is often brief and vague, we established the nature of some input documents through deduction and interpretation. Evidently, Requirements Specification is the most dominant input document type for NLP4RE research. We noticed that some document types are more recent, such as User Feedback, User-Generated Content, Legal & Policy, User Story, and Domain Document. We observed that mining requirements related information from user-generated content such as app reviews [44] and tweets [81] has become a growing trend in NLP4RE research, as the widely availability of this type of text can make it easy to validate and replicate NLP4RE results, a possible solution to the shortage of real requirements data [21].

In addition to different types of textual document, Figure 9 also depicts non-textual documents such as Other Model, Code and UML Diagram, but these types of document are not commonly used. Typically, these documents would need to be pre-processed and paraphrased into a structured textual form before they can be treated by NLP techniques.

![Figure 9: Input document types and the number of studies using each type.](image)

5.4 RQ4: State of Practice in NLP4RE Research

Types of new tool developed. From the reviewed studies that explicitly report new tools, we found 130 named tools. These tools, hence called NLP4RE tools, are presented in Table 9 where they are categorized according to their main NLP4RE tasks. In Table 9, each tool is represented by its name (e.g., OICSI) and indexed by a study identifier (e.g., S678). Through the study identifier of each tool, the reader can locate the reference of the study that reports the tool in Appendix 1. Evidently, the top-ranked tools are modeling (34) and detection (31), followed by extraction (24), classification (20) and tracing & relating (15). At the bottom of the rank is search & retrieval (6).

The greater attention given to the modeling tools reflects the uniqueness and importance of modeling task, as modeling is a fundamental activity in RE and so much so there is a RE phase dedicated entirely to modeling. In addition, modeling entails the combination of both NLP and knowledge representation techniques, thus new tools are needed to support this task. By contrast, other types of tool, especially classification, detection and extraction, may be more readily composed from available NLP technologies and tools. For example, WEKA can be used to support classification, and GATE can be used to support extraction and detection. Consequently research on these tasks may focus on exploring different NLP techniques and tools, rather than on developing new tools. Finally, the limited number of search & retrieval tools can be attributed to the limited attention given to the search & retrieval task.

During our categorization of different tools, we noticed that some extraction tools also support other NLP4RE tasks such as paraphrasing and summarization. For example, extraction tools NAT2TEST and GuideGen perform both extraction and summarization tasks. The latter task is used to compose test cases or test guidelines.

Relationships between NLP4RE tools, NLP4RE tasks and RE phases. We use a circular dendrogram (Figure 10) to show the relationship between these tools and their corresponding RE phases. In this diagram, the NLP4RE tools are first grouped into the clusters by their NLP4RE tasks (the middle layer of the diagram) and then by their targeted RE phases (the inner layer of the diagram). This diagram can be used as a roadmap for us to navigate in both directions: from a given NLP4RE tool to its NLP4RE
task and phase, and from a given RE phase to its tasks and available NLP4RE tools. Using this map, we can ask, for example, which NLP4RE tool is developed for which NLP4RE task and in which RE phase. Based on our results no tools have been found for design phase. Further, this map clearly illustrates the aforementioned *typicality* of NLP4RE tasks versus RE phases.

**Table 9: Categories of NLP4RE Tools**

| Tool Type       | Tool Name (Study ID)                                                                 | No. Tools | Percent   |
|-----------------|--------------------------------------------------------------------------------------|-----------|-----------|
| **Modeling**    | OICSI (S678), NL-OOPS (S553), EA-Miner (S499), CM-Builder (S343), Circe (S34), LIDA (S623), NIBA Toolset (S272), RETNA (S108), aToucan (S909), DBDT (S31), Cico (S34), NL2UML via SBVR (S70), RADD-NLI (S121), SUGAR (S190), GRACE (S208), AREMCD (S219), RUCM (S227), RSLingo (S266), Zen-ReqConfig (S482), TREx (S496), NAPLES (S499), GenLangUML (S551), ConstraintSoup (S600), C&L (S707), AnModeler (S799), SBEAVER (S813), KCMP Dynamisch (S272), Xtext (S20), Kheops (S35), Visual Narrator (S683), ProcGap (S800), FeatureX (S772), CMT & FDE (S261), VoiceToModel (S765) | 34        | 26.15%    |
| **Detection**   | ARM (S861), SREE (S812), RQA (S903), AnaCon (S41), REGICE (S55), NARCIA (S56), LELIE (S75), SRRDirector (S86), MIA (S14), KROSA (S178), NAI (S226), QuARS (S232), CAR (S252), CARL (S298), RAVEN (S303), ReqSAC (S370), RAT (S376), MaramaAIC (S395), RESI (S432), RECAA (S447), DeNom (S448), RETA (S450), AQUASA (S501), Dowser (S644), QAminer (S661), LeCa (S701), S-HTC (S258), CNLP (S464), Pragmatic Ambiguity Detector (S256), ReqAligner (S663), REAssistant (S662) | 31        | 23.85%    |
| **Extraction**  | findphrases (S13), AbstFinder (S307), FENL (S71), NAT2TESTSCR (S131), NLP-KAOS (S132), SAFE (S385), AUTOANNOTATOR (S433), UCTD (S453), GUEST (S598), Guidance Tool (S688), SpecQua (S743), NAT2TEST (S744), semMet (S777), Test2UseCase (S810), OCLgen (S845), Text2Policy (S872), GaussT (S888), SNACC (S891), Doc2Spec (S897), ARSENAL (S915), MaTRex tool (S284), ELICA (S2), CHOR EOS (S520), GuideGen (S907) | 24        | 18.46%    |
| **Classification** | ASUM (S129), RUBRIC (S223), WCC (S257), NFR2AC tool (S306), ALERTme (S332), PUMConf (S337), FFRE (S341), AUR-BoW (S500), SEMIOS (S550), CRISTAL (S629), CoReq (S672), SD (S674), ACRE (S757), SOVA R-T (S778), SMAA (S788), CSLLabel (S892), HeRA (S718), NFR Locator (S758), SURF (S910), NFRFinder (S647) | 20        | 15.38%    |
| **Tracing & Relating** | Coparvo (S24), Trustrace (S25), Histrace (S25), CoChAIr (S26), HYPERDOCSY (S38), ReqSimile (S171), LGRTL (S198), CQV-UML (S400), TiQi (S651), REVERSE (S717), LiMonE (S723), ESPRET (S792), COCAR (S805), RETRO (S934), WATson (S302) | 15        | 11.54%    |
| **Search & Retrieval** | RE-SWOT (S174), IntelliReq (S602), ReqWiki (S711), iMapper (S784), PriF (S802), WIKINA (S686) | 6         | 4.62%     |
| **Total**       |                                                                                      | 130       | 100%      |

**Tool development timeline.** These NLP4RE tools were proposed between 1990 and 2019 and their development timeline is shown in Figure 11. Clearly, before 2004, the development had been patchy, with just 18 tools produced; from 2004 onwards, however, there has been a year-on-year growth of NLP4RE tools, with only a brief dip in 2007. We observe that this growth period corresponds to the strong growth period of NLP4RE research (Figure 3). The number of tools in 2019 is incomplete as our search was completed in April 2019.

**Tool availability.** Only 15 (11.54%) of these tools can be found online (See Table 10). However, of these 15 tools, aToucan requires access permission while IntelliReq is not accessible. For the remaining 13 tools, seven are open source tools hosted respectively on GitHub, SourceForge and a Semantic Wiki; three provide web-interface for users to try and another three can be downloaded from the Internet and installed on user computers. Among these accessible tools, only ReqSimile has stood the test of time, while the others were developed recently. But even ReqSimile is still in Beta version, meaning that it is available for testing before its general release. Clearly, the state of the availability of NLP4RE tools is rather poor.
Figure 10: The 130 NLP4RE tools clustered by NLP4RE tasks and then by RE phases.

Figure 11: Development timeline of NLP4RE tools.
5.5 RQ5: NLP Technologies for NLP4RE

From the studies that make explicit use of NLP technologies (including ML and deep learning algorithms), we extracted and synthesized 231 different technologies, and classified them into 140 NLP techniques (Figure 12), 66 NLP tools (Figure 13) and 25 NLP resources (Figure 14). Clearly, NLP resources form the smallest category, a clear indicator of the lack of resources for NLP4RE research. The usage of each category and its relationships with the NLP4RE tasks are discussed as follows.

Most used and least used NLP techniques. As shown in Figure 12, the most frequently used NLP technique is POS tagging (used by 187 studies), while the next most used techniques are tokenization (by 81 studies), parsing (by 72 studies), stop-words removal (by 70 studies), term extraction (by 68 studies), and stemming (by 68 studies). Figure 12 reveals that most NLP techniques, including those highly used, are syntactic techniques, a strong indicator of their dominance in NLP4RE research. In addition, a large number of techniques are underused, with 63 of them, accounted for 45.00% of the 140 NLP techniques, being only used once or twice.

Most used and least used NLP tools. As shown in Figure 13, the most frequently used NLP tool is Stanford CoreNLP (used by 80 studies), while the next most used tools are GATE (by 35 studies), NLTK (by 23 studies), Apache OpenNLP (by 21 studies), and WEKA (by 13 studies). Among these, apart from WEKA, which is a data-mining tool, the other four tools are general-purpose NLP tools. Figure 13 also reveals a large number of underused tools, of which 42 are only used once and 10 are used twice. This means that 78.79% of the 66 NLP tools have only been used once or twice.

Most used and least used NLP resources. As shown in Figure 14, the most frequently used NLP resource is WordNet (by 66 studies), followed by VerbNet (by 9 studies) and British National Corpus (by 7 studies). Most NLP resources listed in Figure 14 are lexical resources. There are a large number of underused resources, including 12 (or 48%) that are only used once or twice.

Long tail distribution of NLP technologies. The usage of each category of NLP technologies exhibits a distribution pattern known as the “Long Tail” [82]. It means that only a small number of technologies have been used frequently, as described above, whereas the majority technologies have a very low usage. The most frequently used technologies are called the “hits”, whereas the least used are called “long tails”. Clearly, POS tagging, Stanford CoreNLP and WordNet are the hits, indicating their popularity in

| Tool Name          | Tool Type     | Year | Web Address                              | Status                                      |
|--------------------|---------------|------|------------------------------------------|---------------------------------------------|
| aToucan (S909)     | Modeling      | 2015 | https://sites.google.com/site/toucan     | Need access permission                      |
| CMT & FDE (S261)   | Modeling      | 2015 | https://github.com/isti-fmt-nlp/tool-NLPtoFP | Free open source                            |
| Visual Narrator    | Modeling      | 2016 | http://www.staff.science.uu.nl/~alpern/  | Free to try only, with a simple UI         |
| AnModeler (S799)   | Modeling      | 2016 | https://sites.google.com/site/anmodeler/ | Software can be downloaded                  |
| FeatureX (S772)    | Modeling      | 2018 | https://github.com/5quintessential/FeatureX | Open source software                        |
| SpecQua (S743)     | Extraction    | 2014 | http://specqua.org                       | Free to try only, with a simple UI         |
| Text2UseCase       | Extraction    | 2019 | https://sites.google.com/view/text2usecase/home | Web-based application, free to try, professional look and feel |
| GuideGen (S907)    | Extraction    | 2019 | https://github.com/hotomski/guidegen     | Open source software                        |
| Pragmatic Ambiguity Detector (S256) | Detection | 2012 | https://github.com/isti-fmt-nlp/Pragmatic-Ambiguity-Detector | Open source software |
| IntelliReq (S602)  | Detection     | 2014 | http://www.intellireq.org                | Website blocked                             |
| NARClia (S56)      | Detection     | 2015 | https://sites.google.com/site/narclia    | Can be installed on user computers         |
| NFR Locator (S758) | Classification| 2013 | https://github.com/RealSearchGroup/NFRLocator | Open source software |
| PUMConf (S337)     | Classification| 2018 | https://sites.google.com/site/pumconf/   | Can be installed on user computers         |
| ReqSimile (S676)   | Tracing & Relating | 2005 | http://reqsimile.sourceforge.net         | Free open source, Beta version              |
| ReqWiki (S711)     | Search & Retrieval | 2013 | http://www.semanticsoftware.info/reqwiki | Open source web-based application |

Table 10: NLP4RE Tools Available Online
NLP4RE research. However, what is more interesting is the huge number of long tail technologies – particularly those that have only been used once or twice. According to the Long Tail theory [82], such technologies are “niches” in the market, but that is not entirely true of the NLP technologies used in NLP4RE research. Some of the long tail technologies are discussed in the following.

Long tail NLP techniques. Our initial investigation suggests that most long tail NLP techniques are nascent. For example, various deep learning techniques such as Word Embedding, Doc2Vec, LSTM, CNN, and RNN, are novel. It is therefore natural that they have a very low usage. Some long tail techniques are probably out of date or obsolete. For example, Lesk Algorithm, a classical algorithm for word sense disambiguation (WSD), is now being replaced by more advanced WSD techniques [83]. A few long tail technologies are real niches, as they are developed to serve specific needs. For example, CFG Parsing is a formal grammar for regulation expression and SCDV is a specialized technique to support faster construction of feature vectors in ML algorithms. For NLP4RE researchers, nascent techniques provide the springboard for innovation and novelty. In the future there will be more and
more long tail NLP technologies, but only a small number of them will become future hits, according to the Long Tail theory [84].

![Figure 13: 66 NLP tools and their frequency of use.](image)

![Figure 14: 25 NLP resources and their frequency of use.](image)

**Long tail NLP tools.** Most long tail NLP tools are specialized tools. Many of them are taggers (e.g., Genia Tagger, CLAWS POS Tagger and Brill’s POS Tagger) and parsers (e.g., ANTLR Lexical Parser, SEMAFOR Parser and Java SAX Parser). There are also other types of tool, such as Gensim for topic modeling and LingPipe for named entity recognition. We therefore deduce that most long tail NLP tools are niches in the sense they are specialized tools.
Long tail NLP resources. According to our research, long tail NLP resources tend to be domain specific or language specific. For example, VerbOcean is a lexicon for mining semantic verb relations on the web; MODIS and CM-1 are datasets for software engineering\textsuperscript{14}; GermaNet (a lexicon for German language) and Floresta Corpus (a syntactic tree corpus for Portuguese) are Language-specific resources. A few long tail resources are nascent, such as Google News Corpus and DBpedia corpus for Wikipedia. There are also a couple of out of date resources, such as Brown Corpus and Hornby’s Verb Patterns.

Relationship between NLP techniques and NLP4RE tasks. As it is not possible to show the relationship between all the 140 NLP techniques and their supporting NLP4RE tasks, we have chosen 32 top-ranked NLP techniques for discussion. Figure 15 shows these techniques and their frequency of use – each technique has been used at least 10 times. Figure 16 depicts these techniques and their relationships with the six NLP4RE tasks. It shows that these NLP techniques are evenly distributed across all six NLP4RE tasks, revealing a symmetric pattern. This suggests that all these 32 techniques are generally applicable to the six NLP4RE tasks. However, as these techniques are predominantly word-based, we deduce that most current NLP4RE studies are based on baseline NLP techniques, with little consideration to semantic or discourse analysis.

![Figure 15: Frequently used NLP techniques - those that have been used 10 times or more.](image)

Relationship between NLP tools and NLP4RE tasks. As with NLP techniques, we have chosen the top 14 NLP tools for discussion, on the basis that each tool has been used at least three times. Figure 17 shows these tools and their frequency of use. The relationship between these tools and the six NLP4RE tasks is depicted in Figure 18, which shows that most tools are used for detection, classification and extraction, and only a few for modeling, tracing & relating and search & retrieval. The lack of NLP tools for modeling thus supports our early claim that more modeling tools are needed. We noticed that the aforementioned general-purpose NLP tools – that is, Stanford CoreNLP, GATE, NLTK, and Apache OpenNLP – have been used to support all six NLP4RE tasks.

Relationship between NLP resources and NLP4RE tasks. We have chosen 14 NLP resources for discussion, on the basis that each resource has been used at least three times. Figure 19 shows these resources and their frequency of use. The relationship between these tools and the six NLP4RE tasks is depicted in Figure 20, which shows that resources are in general scarce for all the tasks, but particularly so for modeling and search & retrieval. Among these NLP resources, only WordNet has been used to support all six NLP4RE tasks; VerbNet used for all tasks but modeling; British National Corpus used in all but modeling and search & retrieval. We observe that there is a general lack of NLP resources suitable for the NLP4RE tasks.

\textsuperscript{14} These datasets are located at \url{http://promise.site.uottawa.ca/SERepository/datasets-page.html}. Other RE related resources may have been published in short papers and thus have not been included in our study. For example, PURE (See: A. Ferrari, G. O. Spagnolo, and S. Gnesi, “PURE: A Dataset of Public Requirements Documents,” RE 2017) and SEM-REQ (see: W. Alhoshan, R. Batista-Navarro, and L. Zhao, “Towards a Corpus of Requirements Documents Enriched with Semantic Frame Annotations,” RE 2018) have not been included in this mapping study, as they were reported in short papers.
Figure 16: Relationship between frequently used NLP techniques and the 6 NLP4RE tasks.

Figure 17: Frequently used NLP tools - those that have been used three times or more.
Figure 18: Relationship between frequently used NLP tools and the corresponding NLP4RE tasks.

Figure 19: Frequently used NLP resources - those that have been used three times or more.
6. Reflection on the Key Findings and Implications for Future Work

In this section, we first reflect on our key findings to highlight the trends and gaps in the current NLP4RE research; we then use this reflection to motivate the implications for future research and practice.

6.1 Summary of Key Findings and Observations

In this section, we summarize the key findings and observations based on the answers to our five research questions.

6.1.1 The State of NLP4RE Literature

This mapping study has identified 404 primary studies relevant to NLP4RE. The number of studies reflects the importance of the field and the attention it has received from researchers. Although publication timelines indicate that NLP4RE research started more than three decades ago, it was only the last 15 years that the field has grown into an active and thriving area, producing 88% of the total identified studies. Technological advancements in the field of NLP during that period have obviously paved the way for the rapid growth and development in NLP4RE.

Of the studies identified, the majority were conference and workshop papers. Such a trend is consistent with the publication pattern in other RE and SE areas, as some RE and SE conferences such as RE and ICSE are highly competitive and comparable to top journals.

The large number of diverse publication venues for these NLP4RE studies shows that NLP4RE has a core base in RE and a strong audience in SE; it has also attracted a general interest from diverse communities. However, while NLP4RE is an application area of NLP, NLP4RE studies were rarely published at NLP venues and this indicates a lack of awareness of NLP4RE work in the NLP research community.
6.1.2 The State of Empirical Research in NLP4RE

Although different types of research are found from the reported NLP4RE studies, Solution Proposal is the main research type, adopted by 271 (67.08%) studies, followed by Validation Research (17.33%). The remaining research types are less common: Evaluation Research (7.18%), Philosophical & Opinion (4.70%), and Personal Experience (3.71%). Such a trend has also been observed in other areas of RE and SE, which is likely to repeat in the future.

These different research types were evaluated by different evaluation methods and there is a clear alignment between the research types and the evaluation methods used by them. Around 65% of the Solution Proposal studies (175 out of 271) were evaluated using a laboratory experiment (either a LESS or a LEHS) while around 35% of them using an example application. This suggests that none of the solution proposal studies has been evaluated in a real world environment. Lack of industrial case studies and field experiments is therefore a major challenge for NLP4RE research.

6.1.3 The Focus of NLP4RE Research

Of 370 NLP4RE studies relevant to this facet, the majority (42.70%) have targeted at the analysis phase, while only 0.81% have targeted at the design phase. Apart from these two phases, the distribution of the remaining studies puts management and elicitation each at 16.76%, modeling at 16.49%, V&V at 4.05%, and testing at 2.43%. Evidently current NLP4RE research is analysis-centric.

This observation is further supported by our findings that at 26.22%, the detection task, with the main purpose to support the analysis of requirements documents, is the most researched NLP4RE task by the reviewed studies. The remaining studies are more or less evenly distributed among these four tasks: classification (19.73%), extraction (17.03%), modeling (15.95%), and tracing & relating (14.32%). At only 6.76%, search & retrieval is clearly the least studied task.

As we just alluded to, there is a close relationship between the analysis phase and the detection task. This relationship is forged by the main problem in this phase and the NLP solution to this problem. Based on this observation, we identified the following pairs of relationship between the RE phases and the NLP4RE tasks:

- For the analysis phase, the main problem is the detection of language issues in requirements documents. The central NLP4RE task to address this problem is therefore detection. Other tasks, such as classification, extraction, tracing & relating, and search & retrieval, are used to support the detection task.
- For the management phase, the main problem is the identification of traceability relationships between requirements. The central NLP4RE task to address this problem is therefore tracing & relating. Other tasks, including classification, detection, extraction, and search & retrieval, are used to support the tracing & relating task.
- For the elicitation phase, the main problem is the extraction of requirements concepts. The central NLP4RE task to address this problem is therefore extraction. Other tasks, including classification, detection, tracing & relating, and search & retrieval, are used to support this task.
- For the modeling phase, the main problem is the extraction of requirements concepts and the composition of conceptual models. The central NLP4RE task to address this problem is therefore modeling. The extraction task is used to support modeling.

We believe a deep understanding of these intricate relationships between different RE phases and NLP4RE tasks can be valuable for the development of appropriate NLP tools to support RE activities.

After investigating the NLP4RE studies from the perspectives of the RE phases and NLP4RE tasks, we turned our attention to the types of input document processed by these studies. Of the 14 different document types identified, requirements specification is the most commonly processed input document type, used by 239 studies (64.59%). However, we observed that there are some emerging trends towards using other types of document as input, such as user feedback, user-generated content, legal & policy, domain document, and user story. Processing these kinds of document may present new challenges to NLP4RE researchers, not only that such documents would not conform to linguistic or structural standards that are normally expected for requirements specifications [19], but also that such documents would contain unfamiliar vocabulary and concepts to RE. Given years of NLP4RE research, we believe that it is time for researchers to exploit more challenging texts and to explore uncharted territory.
6.1.4 The State of the Practice in NLP Research

From the 370 studies that reported new results, we found 130 tools, of which 26.15% are modeling tools, 23.85% are detection tools, 18.46% are extraction tools, 15.38% are classification tools, 11.54% are tracing & relating tools, and 4.62% are search & retrieval tools. While the development timeline for these tools stretches from 1990 to 2019, the majority of the tools were found between 2004 and 2019. The growth of these tools has followed the same pattern of NLP4RE research over the same period. However, of the 130 tools, only 15 can be found on the Internet. On closer inspection, one of these tools requires access permission and another is not accessible. This left 13 tools with varying degrees of availability. Furthermore, apart from one tool – ReqSimile – which was developed in 2005, the remaining 14 were developed recently, after 2012. This means that 14 out of 15 available tools have not stood the test of time. As stated in Section 1, some companies have only started to develop NLP tools for RE. This shows that there is a huge discrepancy between the current state of the art and the state of the practice in NLP4RE research.

6.1.5 NLP Technologies for NLP4RE Research

A total of 231 different NLP technologies were identified from the selected studies, with 140 NLP techniques, 66 NLP tools and 25 NLP resources. Such a great number shows that NLP is fundamental to NLP4RE. However, these technologies have not been utilized to full potential, with a large amount being used once or twice, equivalent to 40% of the NLP techniques, 78.79% of the NLP tools and 48% of the NLP resources. The key findings on the usages of these NLP technologies are summarized as follows:

- Across the board, POS tagging, Stanford CoreNLP and WordNet are the most frequently used technologies with respect to their categories (namely, technique, tool and resource) – as might be expected, given the popularity of these technologies.
- Most frequently used NLP techniques were developed in the 1990s. Such techniques typically support the low-level syntactic analysis tasks such as POS tagging, tokenization, parsing, stop-words removal, term extraction, stemming, and lemmatization. This probably explains why the majority of the studies have targeted at the analysis phase and focused on low-level NLP4RE tasks such as detection and extraction.
- By contrast, most of the long tail NLP techniques are recent and novel. For example, various word embedding techniques only emerged around 2010 and, in particular, Google’s vector representation of words (Word2Vec) was developed in 2013 [85]. Given the novelty of these techniques, it is therefore natural that only a few studies have used them. On the other hand, the limited attention to these novel techniques may also be attributed to the lack of NLP expertise in NLP4RE.
- General-purpose NLP tools are more popular than specialized tools. Most specialized tools are taggers such as Genia Tagger and CLAWS POS Tagger. This clearly indicates that researchers prefer to use general-purpose tools than specialized tools.
- The number of NLP resources used by NLP4RE studies is small in comparison with the number of NLP techniques and tools; the number of frequently used NLP resources is even smaller, with WordNet as the only predominant resource. There is also a clear lack of RE-specific resources, as apart from MODIS and CM-1, the remaining resources are for general NLP applications.

6.2 Implications for Research and Practice

6.2.1 Implications for Research

Need to collaborate with NLP researchers: NLP4RE appears to be a lively research field especially in the latest years, and it is recognized in the top RE and SE venues. On the other hand, the penetration of NLP4RE research in the NLP field, which is the source of the technologies for NLP4RE, is scarce (see Sect. 5.1). This calls for more synergies between the RE community and the NLP community, and RE researchers are required to make their problems more appealing for NLP researchers. NLP research is often focused on broader linguistic problems (automatic summarization, machine translation, etc.), oriented to generalization over domains, and based on large datasets. NLP4RE research is typically context-specific, domain dependent and datasets are scarce or limited. Challenging NLP researchers to provide solutions in these contrived contexts may be an opportunity to improve cross-fertilization of the disciplines.

Need to apply research results to real-world problems: While NLP4RE counts several solution proposals, evaluated in the lab by means of experiments, the contributions in the form of case studies and even experience reports, which take into account the
contexts of organizations, are more limited (Sect. 5.2). This suggests that NLP4RE researchers should take a step forward and apply the large variety of proposed solutions, which have been validated in lab, to real-world industrial problems.

**Need to expand the research scope beyond the typical RE process:** While most of the RE phases are thoroughly investigated, and especially Analysis, there is more limited research on studies that analyze or manipulate RE artifacts in other software engineering phases such as testing or design. This indicates that opportunities exist to better exploit synergies within the SE community to expand the scope of NLP4RE research also outside the typical RE process.

**Need to identify more NLP4RE tasks:** NLP4RE researchers have sought to address NL issues related to a range of NLP4RE tasks, covering Detection, Extraction, Modeling, Classification, Tracing & Relating, and Search & Retrieval (Sect. 5.3). As most efforts have so far been concentrated on the first four tasks, Search & Retrieval provides a possible area for additional investigation. There may also be other tasks that have not been uncovered by this mapping study, which can be investigated in future research.

**Need to analyze a wider range of RE related documents:** Additional areas of research come from the types of documents that can be considered for evaluation: user stories, use cases, domain documents, interview scripts and models are still marginal in the research, while they have a primary role in practice. Furthermore, although recent research is giving relevant attention to artifacts such as user feedback, legal documents and user stories, the field is still open for further investigation.

**Need more publicly available NLP4RE tools for research validation:** Researchers should address the lack of public availability of most of the tools developed. While on one hand it is important to share data, it is also extremely relevant to make tools publicly available, especially in a context such as RE in which data are often confidential. This can help other researchers build on top of the work of their peers, and would facilitate also technology transfer with industries, as companies often want to see a working tool to be convinced about the feasibility of a collaboration, for example to adapt the tool to the company context.

**Need to develop RE related language resources:** This mapping study shows that NLP4RE research has mostly utilized lexical resources such as WordNet and VerbNet, whereas the use of corporal resources is still rare. The main reason we believe is lack of RE-specific corpora, as currently there are only a few RE or SE specific datasets available, including MODIS and CM-1. Using general-purpose corporal such as British National Corpus and Wikipedia Corpus to train ML algorithms for processing requirements text would lead to unreliable results. Successful corpus-based NLP (or statistical NLP) for RE will depend on the availability of large, annotated requirements corpora. To help evaluate research results, we also need other types of language resources, including shared datasets, benchmark data and performance metrics.

**Need to introduce NLP literacy into RE education and training:** The top NLP techniques identified in Section 5.5 may be useful to instructors in RE education and training, to focus their teaching on specific techniques, tools and resources that are dominant in NLP4RE. Instead, the technologies in the “long tail” (see Sect. 5.5) can give researchers an indication on the new, most recent, technologies (e.g., Word Embedding, Bag-of-Frames, Doc2Vec) that should be taken into account, as they may not have been fully exploited in NLP4RE research. This mapping study has discovered that advances in NLP technologies have a direct impact on the progress in NLP4RE research. NLP4RE researchers should therefore immerse themselves in the learning of new NLP technologies.

### 6.2.2 Implications for Practice

**Need to collaborate with industries for research validation:** A mature software technology should be evaluated on real-world applications or industrial projects, to assess its scalability, practicality and usability. Since case study research in industrial settings is still limited as evaluation method, practitioners should open their doors to evaluate the different NLP4RE solutions made available by the researchers, as most of the RE phases are covered by some proposed solution. In particular, practitioners can leverage solutions oriented to the Analysis phase and for the tasks of Detection and Classification. Furthermore, practitioners can leverage solutions mainly for their software requirements specifications, as this is the type of artifact that is mostly considered by current studies (Figure 9).

**Transfer research results to industrial practices:** NLP4RE research has produced a large number of tools, though mostly are in the category of modeling. Practitioners can find the dendogram in Figure 10 particularly useful to explore which tools have been
developed for their specific needs, in terms of tasks and RE phase. Unfortunately, practitioners have to contact the tool authors to access most of the tools, as only few of them are made publicly available. This is, however, also an opportunity, as generic, context-independent tools may need to be adapted to the specific company context, and general purpose, freely accessible tools that may not work out of the box, thus leading companies to discard the tool as not appropriate for their needs.

Transfer technology know-how to industrial practices: The set of top NLP technologies, including techniques, tools and resources, identified in Section 5.5 may be particularly useful to practitioners who wish to develop in-house NLP4RE tools for their needs, by leveraging existing platforms (Stanford CoreNLP, GATE, NLTK, Open NLP). The top techniques, tools and resources identify the basic, well-established, elements that are needed to practice NLP4RE. It is also interesting to notice that knowing about the top 32 NLP techniques identified (POS Tagging, Parsing, etc.) enables to address the whole set of NLP4RE tasks. This provides practitioners with a clear indication of the knowledge needed to develop NLP4RE tools, and can be useful to identify the skills required during recruitment of personnel that may be dedicated to the in-house development of NLP4RE tools.

7. Study Validity and Limitations

The main threat to the validity of any type of literature review is the question of reliability [86]: if two different studies follow the same research procedures, will they produce the same results [87]? For systematic literature reviews and systematic mapping studies, the threat of reliability can be manifested in the entire review process, from identification of the literature to selection of the relevant papers to the final analysis. To mitigate this threat to the validity of our mapping study, we took some preventive measures in every step of the study process, described as follows.

Reliability of literature search: Due to the constraints on resources, time and search engines, it is almost impossible to find the entire population of all the relevant papers on NLP4RE [86]. To ensure we found as many relevant papers as possible and as close to the actual population as possible, we followed the recommended guidelines [88], [69] to identify the literature (Sect. 4.2.1), formulate the search terms (Sect. 4.2.2) and perform the search (Sect. 4.2.3). However, it is possible that we may have not found those papers whose authors might have used other terms that have not been included in our search terms, though we have tried to mitigate this problem through initial and targeted searches. As our main search phase relied on the search engines provided by our chosen libraries, the quality of the search engines could have influenced the completeness of the identified primary studies, as reported by many other systematic reviewers [89], [72].

Reliability of study selection: To ensure our study selection was as accurate as possible, as free from researcher bias and human errors as possible, we followed a rigorous study selection process, guided by the carefully designed inclusion and exclusion criteria, and enforced by crosschecking and independent checking of the selected and deselected studies (Sect. 4.2.4). We paid attention particularly to the last two stages of study selection to ensure that the data inspectors carefully crosschecked each excluded and included paper. Whenever there was double about the relevance of a paper, we called upon the supervisors for discussion, based on which the final decision was made. We made the decision to exclude short papers in order to obtain a more balanced view of NLP4RE research. This is a limitation of our study. In spite of this, we believe that the study population we identified is close to the actual population and is a good representative sample of the current state of NLP4RE research.

Reliability of data extraction and classification: To ensure we extract the required data and organize the selected studies accurately, consistently and uniformly, we followed a faceted classification scheme with a comprehensive set of predefined categories (Sect. 4.3). However, the classification scheme was not foolproof for data extraction, as this process involved subjective interpretations and decisions by the researchers. Lack of sufficient details about the design and execution of the reported studies often hindered data extraction. A particular problem arising from identifying exact NLP technologies from the studies was the lack of precise, explicit and standard description of these technologies in the reported studies. For example, when a study stated that it used a simple syntactic technique to analyze a document, it could mean POS tagging only or both POS tagging and parsing. Worse still, some studies stated that they performed a tokenization task, but did not say which NLP tools were used to perform this task. To mitigate this problem, we compiled our own in-house NLP dictionary with a list of NLP techniques, NLP tools and NLP resources. This dictionary was then used to guide us in extracting NLP technologies from the selected studies. The process of classifying the various aspects of the selected studies (such as research types, evaluation methods, RE phases, NLP4RE tasks) also involved
subjective decisions by the researchers. To minimize human errors, we carried out regular checks on each category. Whenever there was doubt about the classification of a particular study, we would re-assess that study, re-extract the data and re-classify the data if necessary.

Reliability of data synthesis, analysis and visualization: To ensure the mapping results were as accurate and error-free as possible, we carefully carried out thematic synthesis, descriptive analysis and frequency counting on the extracted data. Thematic synthesis involved standardizing the names of NLP techniques and establishing the types of input document. To synthesize the extracted NLP techniques, we used our NLP dictionary to normalize the names of NLP techniques or combine similar techniques into one. When we discovered new techniques, we also added them to our dictionary. To synthesize input documents, we relied on our knowledge to identify their common types. The synthesized results were reviewed several times and revisions were made to make them as accurate as possible.

8. Conclusion

This article has reported a first-ever systematic mapping study on the landscape of NLP4RE research. From 11,540 search results, 404 primary studies were included in the mapping study and systematically reviewed according to five research questions. These questions interrogate these studies to understand their publication status, state of empirical research, research focus, state of the practice, and finally, usage of NLP technologies. The answers to these research questions show:

- NLP4RE is an active and thriving research area in RE, which has amassed a large number of publications and attracted widespread attention from diverse communities.
- Most NLP4RE studies (67.08%) are solution proposals having only been evaluated using a laboratory experiment or an example application, while only 7.18% of the studies have been evaluated in an industrial setting, which highlights a general lack of industrial validation of NLP4RE research results.
- The biggest proportion (42.70%) of the NLP4RE studies have focused on the analysis phase, with detection as their central linguistic analysis task and requirements specification as their commonly processed document type, indicating the current focus of NLP4RE research.
- A total of 130 new tools have been proposed by the selected studies to support a range of linguistic analysis tasks, but there is limited evidence that these tools have been adopted or accepted by industry, indicating a lack of industrial practice of NLP4RE research results.
- Although a large number of NLP technologies, comprising 140 NLP techniques, 66 NLP tools and 25 NLP resources, have been used by the selected studies, they have not been used to full potential, with a large amount – particularly those novel techniques – being only used once or twice. Frequently used NLP technologies are syntactic analysis techniques, general-purpose tools and generic language lexicons.

These findings have revealed a huge discrepancy between the state of the art and the state of the practice in current NLP4RE research, indicated by insufficient industrial validation of NLP4RE research, little evidence of industrial adoption of the proposed tools, the lack of shared RE-specific language resources, and the lack of NLP expertise in NLP4RE research to advise on the choice of NLP technologies. The findings have also carried many important implications for NLP4RE research and practice. We believe that these implications can be used to drive NLP4RE research agenda. At the top of this agenda should be concrete plans for active collaboration with practitioners to jointly develop and validate NLP4RE tools, for close collaboration with NLP experts to learn and use the cutting-edge NLP technology, and for developing open NLP4RE tools, shared datasets, benchmark data and performance metrics for research evaluation.

In spite of the gaps and limitations, this mapping study also shows that NLP4RE research has made a tremendous progress over the past 15 years, particularly in the areas of publication and tool development. Additionally, recent work in analyzing more challenging documents such as user feedback and legal documents indicates that NLP4RE research has entered a new chapter by taking on more challenging tasks. Furthermore, we noticed that industries have also begun to leverage advanced NLP technologies to develop NLP tools for RE. There is now a real buzz of excitement that NLP4RE research can soon be transformed into a
practical technology to support RE practice.

The mapping results can benefit researchers and practitioners in many ways. For researchers (also including students), the selected studies and their categorization can serve as useful references for further study and deeper analysis; the identified publication venues, particularly those 12 leading venues, can be used to narrow the search space for literature review in this area or for publishing relevant work; the trends and gaps identified from this mapping study have provided many new ideas for research opportunities. Practitioners can leverage the proposed NLP4RE tools for future development and research collaboration. Finally, the identified and synthesized NLP technologies, together with their usage and their relationships with the NLP4RE tasks, have provided a roadmap to help both practitioners and researchers gain a better understanding of what NLP technologies are in use in RE and how they are related. To conclude, we believe this mapping study is an important contribution to the field of NLP4RE, as it has provided a comprehensive overview of NLP4RE research and offered insights for future work.

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