CONFERENCE ON PRODUCTION SYSTEMS AND LOGISTICS
CPSL 2022

3rd Conference on Production Systems and Logistics

# Conceptualization Of The Use Of Artificial Intelligence For Interdependencies Analysis In Requirements Engineering*

Peter Burggräf[1,2], Georg Bergweiler[1], Falko Fiedler[1], Viktor Slawik[1], Jonas Recker[1]
[1]*Chair of Production Engineering / WZL of RWTH Aachen University, Aachen, Germany*
[2]*Chair of International Production Engineering and Management / Siegen University, Siegen, Germany*

**Abstract**

The efficiency in product development is largely determined by the quality of the requirements and the ability of the product design and production planner to analyze them. Interdependencies between multiple requirements identified at an early stage enable a sustainable design of the product as well as the corresponding production system by increasing process efficiency as well as the effectiveness of development processes. However, the necessary analysis of complex interdependencies between requirements of a product and the corresponding production system is time-consuming, error-prone, and highly inefficient when performed manually. Current development processes are based on such manual processes for analyzing requirements in natural language and must therefore be adapted.

This paper describes a methodical approach based on a semi-systematic literature review making the complexity of the interdependencies manageable by using existing approaches and methods in the field of model-based systems engineering (MBSE) as well as natural language processing (NLP). Thereby, a transition from informal requirements represented in natural language to analyzable and structured information, which enable interdependencies modeling for requirement chains, is described. A corresponding framework for analyzing interdependencies in the requirements engineering process is derived.

**Keywords**

Requirements Engineering; Artificial Intelligence; Natural Language Processing; Requirement Chains

## 1. Motivation

The increasing digitalization of the value chain and its technologies support a reduced time to market but also put the automotive industry under increasing pressure to innovate and adapt processes [1]. Increasing volumes of data for requirements engineering during planning processes call for automated approaches for structuring [2]. A large amount of product, as well as production-related data, can be assigned to planning and development processes [3]. Therewith, requirements engineering is a central part of the early design phase in the product development process (PDP) and bears the largest share of cost responsibility, accounting for two-thirds of the total[3][4]. Automated approaches are used increasingly to make requirements and change processes more efficient. In this context, the use of classification techniques and NLP enables a better understanding of relationships between requirements [2]. Technologies from the field of language and image understanding support planning and decision processes as well as the evaluation of large amounts of data [5]. Thereby, NLP enables the interaction between human language and digital information systems [6]. Methods from the field of Machine Learning (ML) have the ability, similar to the human brain, to identify patterns in large amounts of data and to react as a result [7]. While the human brain is characterized by

DOI: https://doi.org/10.15488/12143 publish-Ing. 

* *The paper successfully passed the peer review process but was not presented at a conference.*

associative reasoning, the strength of algorithms lies in their distinct combinatory [7]. To better identify interactions between data and their properties, the use of models is suitable [2]. Models are used as bridges between undesired initial states and the corresponding desired final states and thus serve to solve problems [8]. The problem in requirements engineering emanates not only from the number of requirements but also from the multitude of sources for requirements. This is reflected in the form of information loss or ambiguity in requirements formulated in natural language [9]. The challenges of working in such an environment with a high level of process efficiency can be illustrated by a striking example as follows. The specifications of an aircraft engine contain requirements in the four-digit range [10]. However, a human being can only read an average of 170 words per minute [11]. If a requirement consists of fifteen words, each reading of the requirement specification takes at least one and a half hours. An analysis for correlations or defects such as contradictions etc. is not even included in the estimation. This example shows the enormous potential of automating parts of requirements engineering. It becomes obvious that there is an immense potential to reduce time and costs. During the requirements engineering the considered scope is increased from a part to larger assemblies and system-crossing (e.g. production) requirements are taken into account in addition to product requirements. Following not only inefficiencies but also the risk of quality losses due to a lack of overview of a large number of requirements and their interdependencies need to be avoided.

## 2. Problem statement and research task

As described, the manual and human management of requirements in product development is associated with a high expenditure of time. Lack of documentation and insufficient consistency of change status updates lead to improvisation in the requirements and change management process to a high degree. As a result, product changes take up more than one-third of the total resources in the design phase [12]. By applying data-based methods, parts of the requirements engineering process can be performed more efficiently. Although the necessary data basis already exists, the lack of formalization of technical requirements significantly limits modeling possibilities [2]. The demand for data-based methods is to combine the advantages of NLP, modeling, and ML. On this basis, increasing sets of requirements can be structured and, based on this, interactions can be identified and explicitly represented. The goal of this paper is to provide a framework for exploratory analysis of requirement chains, by applying methods of AI. In doing so, the focus is additionally on answering the following questions:

How can a process modeling framework for the transformation of separate requirements into transparent requirement chains be designed?

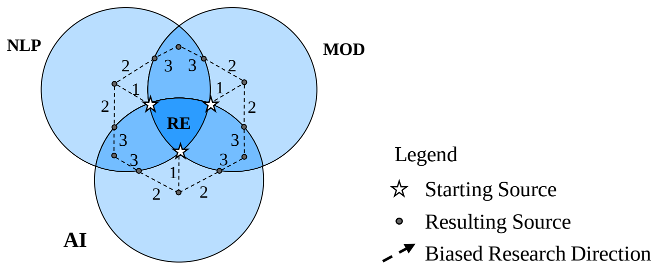
How can existing methods and approaches be classified along with the process modeling?

## 3. Methodical Approach

The content of this paper is part of a research project that uses the research methodology of Design Science Research (DSR). Following this approach, the development of an artifact takes place in the Design cycle between the Relevance cycle and the Rigor cycle [13,14]. Using an abductive approach through the use of an existing knowledge base in the form of existing literature, an artifact is generated through the described framework. This serves to situate the scientific theory within the research project of requirements chain generation.

Along with the process model of DSR, the activities of identifying the problem, defining requirements for the solution, and developing the artifact are thus addressed. A demonstration and evaluation take place in the context of the Rigor cycle since no application takes place in the business environment [15].

To find methods and approaches that fit the problem, a systematic approach for literature review is developed. The approach is based on the snowball principle. It uses the linkage of existing literature via source citations and acts as a cumulative search procedure based on this [16]. Intending to integrate the three identified foci equally, the snowball principle is extended. Figure 1 schematically depicts the developed methodology. The topics NLP, artificial intelligence (AI), and modeling have diverse overlaps in terms of content. Therefore three snowballs are shown, which form intersections in the center. The goal of the search is to link the three topics concerning the application field of requirements engineering, which is located in the center. To consider diverse approaches, the topic of the results is deliberately steered away from the core, and migrations between the fields are provoked. The result of the method is a literature collection with 48 results, whose thematic classification forms a symbolic hexagon around the core topic requirements engineering. From the identified results, the higher-level methods are extracted and promising specific approaches are analyzed.




| Step | Branches Per New Result | New Results |
|---|---|---|
| 0 | | 3 |
| 1 | 3 | 9 |
| 2 | 2 | 18 |
| 3 | 1 | 18 |
| **Sum of Results** | | **48** |

Figure 1: Systematic approach for the literature review

During the literature review, the STARLITE method is used to identify the most promising approaches. Only English titles with the publication year of 2016 or later are considered to focus on recent approaches [17].

The Web of Science database is used to identify a starting dataset. To focus on the core of the problem, a topic-specific search string is developed. This combines the identified topics using the logical operators AND as well as OR. The search string used is given below: TS=(("Requirements Engineering" OR "Requirement Management" OR "Requirements") AND ("MBSE" OR "SysML" OR "UML" OR "Relations") AND ("Artificial Intelligence" OR "Cased Based Reasoning" OR "Machine Learning" OR "Neural Networks") AND ("Natural Language Processing" OR "Natural Language Understanding" OR "Semantic Analysis" OR "Vectorization")). Three results that address the identified three main action areas in addition to requirements engineering are selected as starting sources (step 0 in fig. 1). Thereby, each of the results has the respective focus in one of the three fields. During the search for further results, the database Semantic Scholar is accessed. Starting from the initial dataset, the developed systematic snowball method is applied. Each identified source is considered as a starting point for the identification of further results.

## 4. The State of Research

The following section creates the foundation for conceptualizing the framework for the subsequent explanation and assignment of promising methods based on the systematically compiled literature. After describing the basics of requirements engineering, the fundamentals of modeling are discussed. Finally, basic concepts of AI are explained with a focus on natural language understanding.

### 4.1 Requirements Engineering

Requirements management is an essential part of the PDP. It represents the basis for product planning and development [3]. Requirements are functions or services that products must have to fulfill formal regulations such as standards or contracts [18]. They are defined at the beginning of the project and form a benchmark for later work in the product planning process. For this reason, requirements must be continuously checked and adapted if necessary [3]. To ensure the completeness and structure of the requirements collection, careful identification of all stakeholders involved is essential. Suppliers, laws and standards, production, sales, and controlling are sources of requirements. The most important sources are the market and the customer [19].

While documenting information, an appropriate format must be used in addition to appropriate labeling. Furthermore, a review of the input for suitability should take place [20]. In this context, the natural language documentation of requirements comes into focus. As a basis for documentation, the required performance of sourced products is recorded in a requirements specification. Based on the requirement specification, the contractor creates a requirement specification, which precisely defines the realization project to be developed [8]. Furthermore, documentation in the form of a requirements list is recommended, because requirements can be compared and prioritized [21]. High quality of the requirements documentation can be achieved by easily applicable formulation rules. These concern, among other things, sentence structure, sentence scope, and unambiguity of word choice [22]. To minimize the effort of the documentation process, requirements templates can be used. These provide a clear sentence structure for different types of requirements [9]. Attention must be paid to the initially identified requirements throughout the project. In addition to documentation, they also need to be communicated, maintained, and taken into account when evaluating concepts [19]. Following prioritization, they are compared over the entire development process and specifically introduced into the functional, activity, and construction levels based on the Munich Product Concretization Model [19]. Meanwhile, many external and internal factors have an impact on product development. For this reason, supporting the PDP with information technology is evident. This helps to ensure consistency of documentation, rapid exchange of results, and better traceability of activities [8].

### 4.2 Modelling

Models are an important part of engineering. They contain the foundations for databases in the form of logic, machine theory, and schemes [23]. Thereby, models are representations of a natural or artificial original based on abstractions [24]. During modeling, a limited set of attributes is transferred. Some attributes of the original are excluded. In return, new attributes are included in the developed model [24]. Models can be used as a basis for the development of products and support the solution of complex problems. Model-based development is based on models consisting of machine code and replaces handwritten texts [25]. Due to technological progress, products become more complex. This circumstance requires a more extensive system landscape [26]. Systems engineering (SE) supports the structuring of complex systems. It refers to the documentation of requirements concerning the holistic development picture [27]. MBSE combines the model character with SE. The goal is the transformation of heterogeneous product models into interconnected as well as consistent images of the products [28]. In addition to the model architecture and the behavior of components, requirements are also introduced at each abstraction level of a model [29]. In the environment of the MBSE, one speaks of a model as soon as it fits a given formal form. This is achieved as soon as structures and relationships can be derived automatically from given models [29]. For the construction of models in different industries, the modeling language UML was developed. Through the integrated extension mechanism, application-specific add-ons can be integrated [27]. In this context, SysML has emerged as a dialect of UML. SysML helps in describing structures, behaviors, and requirements of a system. The modeling language extends the repertoire of UML diagrams to be used by integrating requirements diagrams and associated relationship capabilities [29]. Diagrams visualize specific characteristics of the comprehensive model. The focus during filtering is set on defined viewpoints [25].

### 4.3 Artificial Intelligence

Nowadays, both requirements engineering and model-based development involve many manual steps. In the process, humans fall back on vague and incomplete information from their memory [5]. The growing amount of data due to more complex products further complicates human work. The application of specific knowledge is essential for efficient processes. Knowledge is created by interpretation from information, which is aggregated from data by working out relationships [7]. Therefore, accurate analysis of the data sets is essential. For this purpose, the enormous computing power of information systems is increasingly used for data processing [7]. The area of text processing is covered by NLP. By using algorithms, the transformation of natural language texts into machine-readable code is possible [30]. For this purpose, the linguistic levels of natural language texts must be analyzed [31]. The richness of semantics increases due to the integration of relations and relationships between individual words, thus representing the core of language understanding [6]. In addition to NLP, ML forms an important application area of AI research. Its efficient operation is based on a large amount of data [7]. For this reason, ML is closely related to the field of data mining. Data mining describes the extraction of knowledge from aggregated data. In the application field of language, data mining is also referred to as text mining. Text mining includes tasks such as classification of texts and identification of similar texts [32]. Different types of neural networks are used for fast and efficient information processing in the field of ML. They are characterized by their decentralized as well as the parallel structure and their learning ability [7]. The approach of neural networks is optimized by different types of learning initially or continuously. Supervised, unsupervised, partially supervised or self-supervised learning methods are used as well as reinforcement learning [6].

## 5. Conceptional Design of the Framework

The basics compiled above form the foundation for the systematic development of a solution space for the generation of requirement chains. With the help of higher-level concepts of model theory, a concept is first developed that describes the target states of the solution process. Subsequently, the concept is detailed by integrating specific solution increments and an application-oriented framework is presented.

### 5.1 Concept

The goal of the framework is to efficiently extract the existing relationships between separate technical requirements formulated in natural language from the diversity of a collection of requirements. Figure 2 shows the step-by-step procedure during the concept development of the framework.

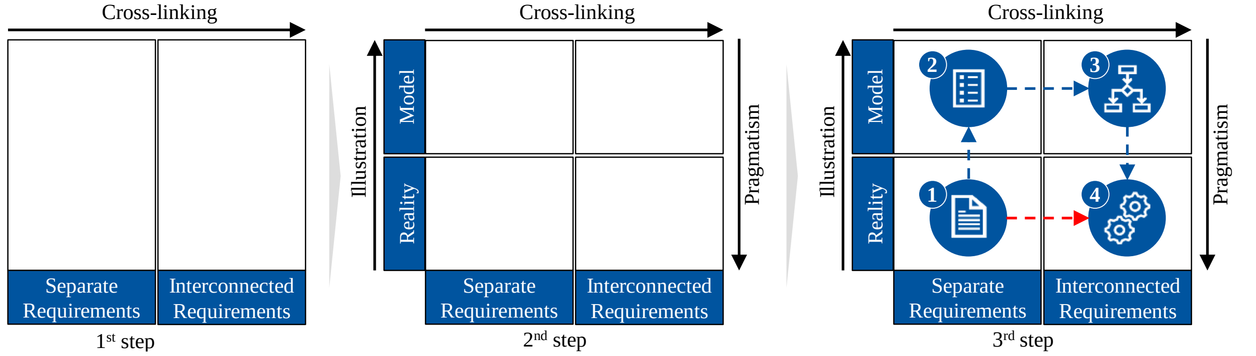



Figure 2: Step-by-step development of a concept for the regulatory framework

In a first step, a clear distinction between separate and non-structured requirements must take place. Before the existing relationships can be recognized automatically, each instance involved must fulfill the prerequisites required for this. The mechanism for linking the separate requirements is defined as cross-linking. In the second step, the model world is detached from reality. In the sense of the modeling idea, an issue can be mapped in the model level to open up new solution possibilities by abstracting a complex issue [24]. Thereby, illustration enables the transition from reality to the model [33,34]. In contrast, pragmatism serves to render the model in reality in a way that is understandable to the interpreter [24]. The two identified boundaries divide the solution space into four quadrants. Each quadrant is characterized by the unique combination of two characteristics determined in the first two steps. For each of the quadrants, a target state is defined in a third step. The overall goal is to analyze relationships between requirements to generate requirement chains. As a result, the separate natural language written requirements form the initial state (1) and the human-comprehensible representation of requirement chains (4) form the target state of the process. The goal of the transition into the model world is the structuring of the separate requirements (2). The goal of the networking of the separate requirements are cross-system requirement chains (3).

### 5.2 Detailed Framework

To detail the concept, the target states must be described by applicable processes. The transition between the first two target states is handled by modeling [33,34]. This comprises the transformation from continuous text, the structuring, and categorization as well as the formalized representation of the requirements formulated in natural language. The result is syntactically decomposed requirements in a machine-readable format. These contain additional information about the sentence-internal relationships between individual language elements. The subsequent cross-linking is the mechanism of the process evaluation. During this process, the identification of direct as well as indirect relationships between requirements takes place. Similarities between language elements are analyzed. In addition, higher-level relationships among subsystems are captured. The result are complex requirement networks, which contain a multiplicity of requirement chains. The discussion of relations takes place with the help of semantic information from semantic memory. This contains application-specific language relationships with increasing semantic richness and can be continuously extended. With the help of the process transfer the last target state can be reached [33,34]. By filtering information using perspectives and views as well as the automatic creation of diagrams, a human-readable visualization of the relationships is created. The resulting framework is given in Figure 3.

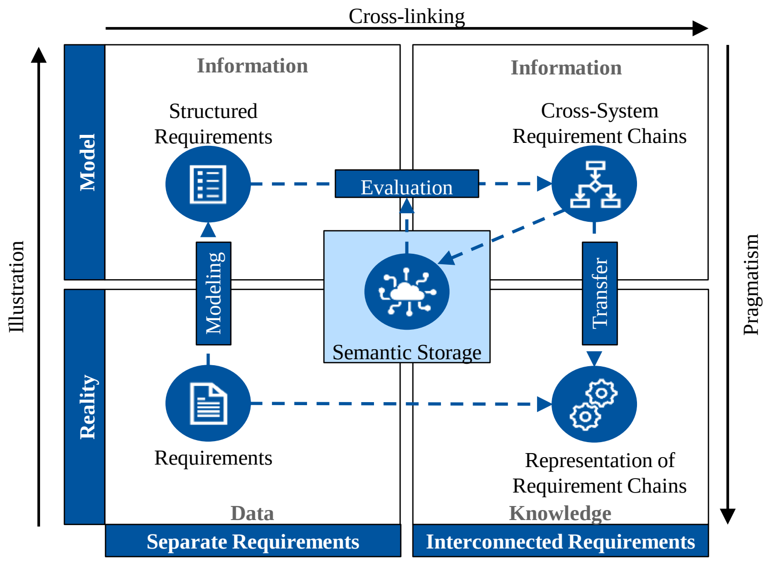



Figure 3: The process modelling framework

### 6. Research Gap

With help of the results of the literature research and the framework, promising approaches for solving the problem can be identified. Subsequently, a summary of the approaches and methods is given in form of a map of methods to identify gaps on the solution path and to formulate research needs based on this.

### 6.1 Map of Methods

The result of the literature research is an extensive landscape of methods with approaches from different areas of industry. To systematically represent the core topics, a method map is shown in Figure 4. This is intended to provide an overview of the approaches identified and to assist the reader with orientation. The systematic design of the research is reflected on the map in the form of the three snowballs NLP, AI, and modeling. The field of requirements engineering is not shown because it represents an ongoing closely linked parallel process. The Requirements field is the starting point for different paths across the map, which end in the Diagrams and Views area. To establish the reference to widespread standard solutions in the area of information technology, the complex AI solutions fastText and BERT are additionally located on the method map.

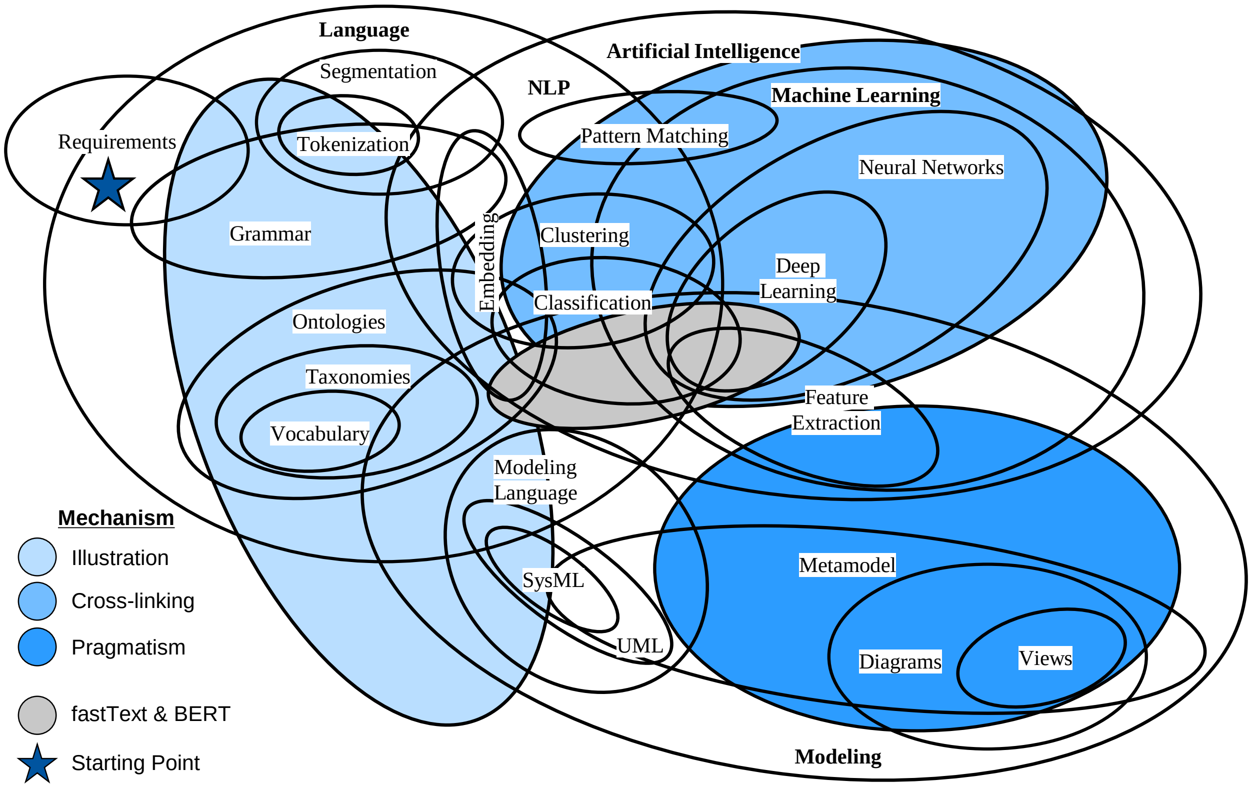



Figure 4: Map of methods

The area of illustration is particularly characterized by approaches from NLP. The systematic decomposition of requirements serves the transformation into the machine-readable domain. BASHIR ET AL., ARORA ET AL., BEN ABDESSALEM ET AL., KOCHBATI ET AL., and XU ET AL. [35][36][37][38][39] take up the methods of segmentation as well as parsing, which represent standard solutions. Based on this, ARORA ET AL. [36] describe an activity to find rule-based relationships between sentence members in a sentence. Using embeddings and similarity computation, CAMPOS ET AL. [40] and DALPIAZ ET AL. [41] filter duplicates and synonyms from the decomposed sentences. ROSADINI ET AL. [42] extends the ideas and uses parsing to predict defects in requirements. In the area of networking, activities of classification and clustering are particularly located. Classification is done by ZHOU ET AL. [43], basis for these methods provides the use of strategies from the field of neural networks and Deep Learning. ZHONG ET AL., KOWSARI ET AL., and ZHOU ET AL. [44][45][46] deal with special forms of neural networks. Different types are combined to increase efficiency and different ML methods are compared. The approaches from ZHOU ET AL. and MENG ET AL. [43][47] deal with classification based on multiple criteria. BEN ABDESSALEM ET AL. [37] and ZHONG ET AL. [44] compare the imported requirements with constructed patterns in a pattern-matching activity. According to the framework, the cross-linking of requirements takes place simultaneously with the usage of semantic information from semantic storage. While KUMAR ET AL. [48] deal with the design of ontologies from taxonomies, ZHANG ET AL. [49] use ontologies to extract semantic information. ZHOU ET AL. [46], extended ontologies by sub-ontologies. BASHIR ET AL. [35] andYANG ET AL. [50] address activities that concern the networking of requirements. To bundle the results in a final step, the design of human-readable visualizations and the application of views are mostly used in the pragmatics domain. Visualizations in the form of a Venn diagram are generated by the approach in DALPIAZ ET AL. [41]. LUCASSEN ET AL. and DALPIAZ ET AL. [51][52][41] present approaches to filter visualizations afterward and to focus or hide areas. To complement this, LUCASSEN ET AL. [51] address the highlighting of different links. Finally, YANG ET AL., ROBEER ET AL., GULIA ET AL., KOCHBATI ET AL., PEREZ ET AL. [50][53][54][37][55] present methods and activities that enable the automatic creation of diagrams.

## 7. Summary and Outlook

This paper presents a framework for process modeling in the AI-supported generation of chains of requirements formulated in natural language. Based on existing methods and approaches, a framework is designed that describes the intermediate states, mechanisms, and tools on the way from separate requirements to cross-system requirement chains. With the help of systematic literature research approaches from the three topic areas NLP, AI and modeling are compiled. Subsequently, representative approaches and results are presented in the form of a method map. In connection with the regulatory framework, it is thus considered which solutions can enable the selected project in a bottom-up manner. Due to the pronounced heterogeneity of the identified approaches, no explicit comparison criteria could be identified. As a result, it can be stated that a bottom-up approach based on a methodology developed in the use of existing approaches does not seem to be very effective. In future work, activities and states within the respective methods must be analyzed and, in a top-down approach, the necessary target states in the regulatory framework must first be described with sufficient precision so that the identified approaches can be compared. Especially the area of evaluation with associated networking methods from the field of neural networks is to be investigated in more detail.

## References


[1] Proff, H., Fojcik, T.M., 2018. Mobilität und digitale Transformation. Springer, Wiesbaden.

[2] Schuh, G., Bergweiler, G., Fiedler, F., Slawik, V., Ahues, C., 2021. A Review Of Data-Based Methods For The Development Of An Adaptive Engineering Change System For Automotive Body Shop. Conference on Production Systems and Logistics.

[3] Eigner, M., Stelzer, R., 2013. Product Lifecycle Management: Ein Leitfaden für Product Development und Life Cycle Management. Springer, Heidelberg.

[4] Ehrlenspiel, K., 2017. Integrierte Produktentwicklung. Carl Hanser Verlag, München.

[5] Görz, G., Schmid, U., Braun, T. (Eds.), 2020. Handbuch der Künstlichen Intelligenz. De Gruyter, Berlin, Boston.

[6] Warschat, J. (Ed.), 2020. Innovation durch Natural Language Processing: Mit Künstlicher Intelligenz die Wettbewerbsfähigkeit verbessern. Carl Hanser Verlag, München.

[7] Mockenhaupt, A., 2021. Digitalisierung und Künstliche Intelligenz in der Produktion. Springer, Wiesbaden.

[8] Verein Deutscher Ingenieure. VDI 2221 - Blatt 1: Entwicklung technischer Produkte und Systeme.

[9] Rupp, C., SOPHISTen, 2014. Requirements-Engineering und -Management. Carl Hanser Verlag, München.

[10] Aunkofer, B., 2009. Anforderungsmanagement. Der Wirtschaftsingenieur. https://www.der-wirtschaftsingenieur.de/index.php/anforderungsmanagement/.

[11] Radner, W., 2000. Ein neues visuell-akustisch gestutztes Computeranalyseverfahren. Spektrum der Augenheilkunde, 239–243.

[12] Schuh, G., Stölzle, W., Straube, F., 2008. Anlaufmanagement in der Automobilindustrie erfolgreich umsetzen. Springer, Heidelberg.

[13] Hevner, A.R., 2007. A Three Cycle View of Design Science Research. Scandinavian Journal of Information Systems 19 (2), 87–92.

[14] Hevner, A.R., March, S.T., Park, J., Ram, S., 2004. Design Science in Information Systems Research. MIS Quarterly 28 (1), 75–105.

[15] Peffers, K., Tuunanen, T., Rothenberger, M.A., Chatterjee, S., 2007. A Design Science Research Methodology for Information Systems Research. Journal of Management Information Systems 24 (3), 45–77.

[16] Heß, J., 2021. Regionale Erfolgsfaktoren entlang des Gründungsprozesses. Springer, Wiesbaden.

[17] Booth, A., 2006. ‘‘Brimful of STARLITE’’: toward standards for reporting literature searches. Journal of the Medical Library Association 94 (4), 421–430.

[18] Deutsches Institut für Normung e.V., 2009. DIN 69901, Projektmanagement – Projektmanagementsysteme – Teil 5: Begriffe.
[19] Ponn, J., Lindemann, U., 2011. Konzeptentwicklung und Gestaltung technischer Produkte. Springer, Heidelberg.
[20] Deutsches Institut für Normung e.V., 2015. DIN EN ISO 9001: Qualitätsmanagementsysteme.
[21] Verein Deutscher Ingenieure. VDI 2222: Methodisches Entwickeln von Lösungsprinzipien.
[22] Grande, M., 2011. 100 Minuten Für Anforderungsmanagement: Kompaktes Wissen Nicht Nur Für Projektleiter und Entwickler. Springer Vieweg, Wiesbaden.
[23] Hesse, W., Mayr, H.C., 2008. Modellierung in der Softwaretechnik: eine Bestandsaufnahme. Informatik Spektrum 31 (5), 377–393.
[24] Stachowiak, H., 1973. Allgemeine Modelltheorie. Springer, Wien.
[25] Schulze, S.-O., Schneider, A., Ackva, S. (Eds.), 2016. Erfüllung von Automotive SPICE Prozessanforderungen mittels modellbasierter Entwicklungstechniken. Carl Hanser Verlag, München.
[26] Sandmaier, H., 2019. Skalierung der physikalischen Gesetze und mathematischen Modellierung. Springer, Heidelberg.
[27] Weilkiens, T., 2006. Systems engineering mit SysML/UML. The MK/OMG Press, Heidelberg.
[28] Albers, A., Bursac, N., Scherer, H., Birk, C., Powelske, J., Muschik, S., 2019. Model-based systems engineering in modular design. Des. Sci. 5.
[29] Alt, O., 2012. Modellbasierte Systementwicklung mit SysML. Carl Hanser Verlag, München.
[30] Paaß, G., Hecker, D., 2020. Künstliche Intelligenz. Springer, Wiesbaden.
[31] Pfister, B., Kaufmann, T., 2017. Sprachverarbeitung. Springer, Heidelberg.
[32] Ertel, W., 2021. Grundkurs Künstliche Intelligenz. Springer, Wiesbaden.
[33] Heimes, H.H., 2014. Methodik zur Auswahl von Fertigungsressourcen in der Batterieproduktion. Aachen, Techn. Hochsch., Diss., 2014. Apprimus-Verl., Aachen.
[34] Maue, A., 2015. Aufwandsorientierte Gestaltung des Produktionsanlaufs am Beispiel der Automobilproduktion. Aachen, Techn. Hochsch., Diss., 2014. Apprimus-Verl., Aachen.
[35] Bashir, N., Bilal, M., Liaqat, M., Marjani, M., Malik, N., Ali, M. Modeling Class Diagram using NLP in Object-Oriented Designing. National Computing Colleges Conference, 1–6.
[36] Arora, C., Sabetzadeh, M., Briand, L., Zimmer, F., 2016. Extracting domain models from natural-language requirements. MODELS '16, 250–260.
[37] Ben Abdessalem Karaa, Wahiba, Ben Azzouz, Zeineb, Singh, A., Dey, N., S. Ashour, A., Ben Ghazala, H., 2016. Automatic builder of class diagram (ABCD): an application of UML generation from functional requirements. Softw. Pract. Exper. 46 (11), 1443–1458.
[38] Kochbati, T., Li, S., Gérard, S., Mraidha, C., 2021. From User Stories to Models: A Machine Learning Empowered Automation, 28–40.
[39] Xu, X., Cai, H., 2021. Ontology and rule-based natural language processing approach for interpreting textual regulations on underground utility infrastructure. Advanced Engineering Informatics 48.
[40] Campos, R., Mangaravite, V., Pasquali, A., Jorge, A., Nunes, C., Jatowt, A., 2020. YAKE! Keyword extraction from single documents using multiple local features. Information Sciences 509, 257–289.
[41] Dalpiaz, F., van der Schalk, I., Lucassen, G., 2018. Pinpointing Ambiguity and Incompleteness in Requirements Engineering via Information Visualization and NLP. Requirements Engineering: Foundation for Software Quality 10753, 119–135.
[42] Rosadini, B., Ferrari, A., Gori, G., Fantechi, A., Gnesi, S., Trotta, I., Bacherini, S., 2017. Using NLP to Detect Requirements Defects: An Industrial Experience in the Railway Domain. Requirements Engineering: Foundation for Software Quality 10153, 344–360.
[43] Zhou, P. and El-Gohary, N., 2016. Domain-Specific Hierarchical Text Classification for Supporting Automated Environmental Compliance Checking. J. Comput. Civ. Eng. (30).

[44] Zhong, B., Xing, X., Luo, H., Zhou, Q., Li, H., Rose, T., Fang, W., 2020. Deep learning-based extraction of construction procedural constraints from construction regulations. Advanced Engineering Informatics 43, 1–14.
[45] Kowsari, K., Heidarysafa, M., Brown, D.E., Meimandi, K.J., Barnes, L.E., 2018. RMDL: Random Multimodel Deep Learning for Classification. ICISDM '18, 19–28.
[46] Zhou, P., El-Gohary, N., 2016. Ontology-Based Multilabel Text Classification of Construction Regulatory Documents. J. Comput. Civ. Eng. 30 (4), 1–13.
[47] Meng, R., Zhao, S., Han, S., He, D., Brusilovsky, P., Chi, Y., 2017. Deep Keyphrase Generation. Proceedings 55th Annual Meeting of the Association for Computational Linguistics 2017, 582–592.
[48] Kumar, N., Srinathan, K., Varma, V., 2016. A graph-based unsupervised N-gram filtration technique for automatic keyphrase extraction. Int. J. Data Mining, Modelling and Management 2016 (8).
[49] Zhang, Jiansong, El-Gohary, Nora M., 2017. Integrating semantic NLP and logic reasoning into a unified system for fully-automated code checking. Automation in Construction 2017 (73), 45–57.
[50] Yang, Z., Bao, Y., Yang, Y., Huang, Z., Bodeveix, J.-P., Filali, M., Gu, Z., 2021. Exploiting augmented intelligence in the modeling of safety-critical autonomous systems. Form. Asp. Comput. 33 (3), 343–384.
[51] Lucassen, G., Robeer, M., Dalpiaz, F., van der Werf, J.M.E.M., Brinkkemper, S., 2017. Extracting conceptual models from user stories with Visual Narrator. Requirements Eng 22 (3), 339–358.
[52] Lucassen, G., Dalpiaz, F., van der Werf, J.M.E.M., Brinkkemper, S., 2016. Visualizing User Story Requirements at Multiple Granularity Levels via Semantic Relatedness 9974, 463–478.
[53] Robeer, M., Lucassen, G., van der Werf, J.M.E.M., Dalpiaz, F., Brinkkemper, S., 2016. Automated Extraction of Conceptual Models from User Stories via NLP, in 2016 IEEE 24th International Requirements, pp. 196–205.
[54] Gulia, S., Choudhury, T., 2016. An efficient automated design to generate UML diagram from Natural Language Specifications. 6th International Conference - Cloud System and Big Data Engineering, 641–648.
[55] Pérez-Soler, S., Guerra, E., Lara, J. de, Jurado, F., 2017. The Rise of the (Modelling) Bots: Towards Assisted Modelling via Social Networks. IEEE/ACM International Conference on Automated Software Engineering 32, 723–728.

**Acknowledgments**

The authors wanted to thank the Federal Ministry for Economic Affairs and Climate Action for funding the project *KIZAM – Künstliche Intelligenz im Ziele- und Anforderungsmanagement* on basis of a decision of the German Bundestag that made the presented research possible.

**Biography**

**Peter Burggräf** (*1980) holds the Chair of International Production Engineering and Management at the University of Siegen since 2017. Together with Günther Schuh, he also heads the Factory Planning department at RWTH Aachen University and is Managing Director of StreetScooter Research GmbH.

**Georg Bergweiler** (*1981) is head of the department of Vehicle Production at Laboratory of Machine Tools and Production Engineering WZL of RWTH Aachen University.

**Falko Fiedler** (*1988) is group lead body shop at the department of Vehicle Production at Laboratory of Machine Tools and Production Engineering WZL of RWTH Aachen University.

**Viktor Slawik** (*1994) is a research associate at the department of Vehicle Production at Laboratory of Machine Tools and Production Engineering WZL of RWTH Aachen University.

**Jonas Recker** (*1998) is a student at the department of Vehicle Production at Laboratory of Machine Tools and Production Engineering WZL of RWTH Aachen University.