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# Past, current and future trends in enterprise architecture—A view beyond the horizon

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ABSTRACT

Since its introduction in the late nineteen eighties, the discipline of Enterprise Architecture (EA) has evolved into a well-known practice of managing information systems in alignment with business interests. The evolution of the discipline is reflected in the many available scientific publications. Within a timeframe of three decades, we identify approximately 4000 journal articles and conference papers of which enterprise architecture is a major topic. We conduct a holistic, systematic literature review using artificial intelligence technologies such as information retrieval, text mining and supervised learning, side-by-side with manually reading of many relevant articles. For the first time, we present a holistic historical overview of the scientific development of the discipline. We describe the current focus of enterprise architecture and make suggestions for future publications and conferences using predictive analytics.

As a major result of our analysis, we find that the focus of EA research has shifted from understanding EA in the early years to managing EA today. Furthermore, we identify and investigate several current EA trend topics: We find Cloud Computing to be the trend with the strongest impact on EA and predict that this will be the case until 2020. According to our forecast, the Internet of Things will be the trend with the strongest growth in its impact on EA. Moreover, based on a comparison with the Gartner Hype Cycle, we observe a discrepancy between EA trends in academic work versus practical experiences, which presents a starting point for future research.



**Contents**

1. Introduction . . . 71
2. Background . . . 72
   2.1. Enterprise architecture . . . 72
   2.2. State-of-the-Art reviews on enterprise architecture . . . 72
   2.3. Text mining as a part of artificial intelligence work . . . 72
3. Applying text mining to enterprise architecture research . . . 73
   3.1. Text mining process model for literature reviews . . . 74
   3.2. Information retrieval: publication search and selection process . . . 75
4. History of research on enterprise architecture . . . 76
   4.1. Taxonomy for enterprise architecture research . . . 76
   4.2. Shift from enterprise architecture to enterprise architecture management . . . 76
5. Current and future enterprise architecture research trends . . . 77
   5.1. Identifying, measuring and forecasting current EA trends . . . 77

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0166-3615/

5.2. Understanding the context of current EA trends . . . 78
5.3. Closer look at individual EA trends . . . 78
5.3.1. Cloud computing and enterprise architecture . . . 78
5.3.2. Adaptive or agile enterprise architecture . . . 80
5.3.3. Sustainability and enterprise architecture . . . 80
5.3.4. Smart machines and enterprise architecture . . . 80
5.3.5. Internet of things and enterprise architecture . . . 80
5.3.6. Big data and enterprise architecture . . . 81
5.3.7. Entrepreneurship and enterprise architecture . . . 81
5.3.8. Complexity theory and enterprise architecture . . . 81
6. General discussion and conclusions . . . 81
Acknowledgements . . . 82
References . . . 82

## 1. Introduction

Since the late nineteen eighties, the concept of Enterprise Architecture (EA) has evolved as a discipline and as a method for coping with the management of information systems and the corresponding business elements within complex organisations [1,2]. Today, a variety of practices and frameworks are available that help manage existing architectures of enterprises and support the transition from a current to a future state [3–5].

EA has been and still is a constantly evolving discipline, which is shaped by social progress, technological advances and learning outcomes [6]. Three decades of research on the subject have resulted in many scientific contributions that cover a broad thematic spectrum. Although there are multiple state-of-the-art reviews on EA [3,7–15] that describe and assess the current state of research, none of them comprehensively cover the enormous number of available publications. To address this research gap, it was necessary to conduct the analysis that is presented in this article. We hereby illustrate how related research aspects have changed over time and may change in the near future. We consider our results to be relevant for both EA scientists, who can leverage our findings to design future studies, and EA practitioners, who can consult our analysis to better understand how academic EA trends relate to practice.

Our methodology combines artificial intelligence technologies such as text mining and natural language processing with traditional full-text reading approaches. We apply state-of-the-art text mining techniques to systematically address multiple questions on the past, present and, to some extent, future of scientific research on EA. This approach enables us to comprehensively review the vast number of publications (approximately 4000 journal articles and conference proceedings) that emphasize enterprise architecture. Consequently, this article presents the first holistic literature review that covers EA from its beginning until today. Fig. 1 presents a summary of the publications we identified and analysed.

The results that are described in this article address the following two research questions:

1) What is the current focus of Enterprise Architecture research and how did it change over time?
The first question considers subtopics that are related to EA since it was introduced in the 1980s. We apply a semi-supervised approach in which we use classification schemes and related search queries that have been selected according to earlier reviewers to obtain a holistic view and to evaluate how the focus of EA research has changed over time.
2) What are the current and future Enterprise Architecture research trends?

Question two focusses on today's EA research trends. We identify current trends that appear to be having a major impact on the discipline of EA. We analyse how they have developed in recent years and predict how they will evolve in the future. In addition, we identify similarities and differences between findings from our analysis and the Gartner hype cycle for enterprise architecture.

The remainder of this article is structured as follows: In Section 2, we present the background of our research. In particular, we describe EA as a discipline and present the foundations of the text mining technologies that we implement for subsequent analysis. Section 3 describes the methodology and process that we apply to conduct our literature review. Sections 4 and 5 address the aforementioned questions and present our findings. Finally, the conclusions of our findings and proposal for further research are presented in Section 6.

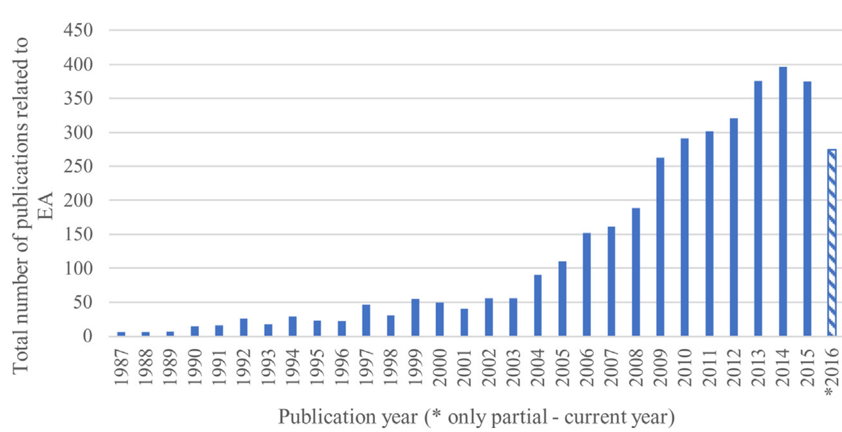


**Fig. 1.** Overview of publications related to Enterprise Architecture by publication year.

## 2. Background

In this section, background information on the topics that are addressed in this article is provided. First, we present the definition of EA, which we use throughout the work, followed by a summary of existing state-of-the-art literature reviews. Afterwards, we present artificial intelligence methods and techniques, which are the foundation for our analysis.

### 2.1. Enterprise architecture

Various definitions or descriptions of Enterprise Architecture exist: The initial idea of applying architecture in the context of enterprises to describe, understand, represent and design different dimensions was developed and made popular simultaneously by different groups in the late eighties and early nineties [6,15]. As a consequence, several EA frameworks emerged [5], which is also a reason for the plurality of definitions of EA. These definitions often vary in terms of the purpose and scope of EA [16,17].

One frequently referenced basis is the ISO/IEC/IEEE 42010:2011 standard, which defines architecture as: “The fundamental organization of a system, embodied in its components, their relationships to each other and the environment, and the principles governing its design and evolution” [18]. This definition can be applied to EA by viewing an enterprise as a “system”. The result is a commonly used definition for EA, which is, for example, embraced in the TOGAF framework, which is one of the most popular EA frameworks [4,19]. This study also embraces the ISO/IEC/IEEE 42010:2011 definition and considers EA to be a discipline that manages the architecture of an enterprise, thereby resulting in the following definition: *“Enterprise Architecture is a discipline that manages the fundamental organization of an enterprise, which is embodied in its components, their relationships to one another and the environment, and the principles that govern its design and evolution.”*

Based on the definition above, EA appears to be specifically concerned with the level of an entire organization where business aspects are included. However, EA is not supposed to solely create a holistic and detailed model of the entire enterprise but relies on various architecture subdomains, which deliver aggregates [8,20]. Therefore, a major concern of EA is to integrate the various architectural domains on which it depends [21]. Other architectural disciplines such as Information Systems (IS) Architecture and Information Technology (IT) Architecture perform similar integrative tasks on lower levels and therefore can be considered parts of an extended EA. In our study, we take this extended view of EA as a basis, which is in line with our objective of providing a view beyond the horizon on EA. Fig. 2 summarizes the described narrow and extended views of EA and outlines how they relate to different architectural subdomains.

### 2.2. State-of-the-Art reviews on enterprise architecture

Ever since the introduction of the discipline, many publications that are related to EA have been written by both scientists and practitioners. We identified several state-of-the-art reviews on EA – “state-of-the-art” hereby means by manually selecting a set of papers or by additional statistical analysis. The origins of EA are analysed and presented by Kotusev [15]. He concludes that the history of EA goes back to the 1960s and that the article by Zachman [1] from 1987, which is commonly referred to as the founding paper of EA, is only a milestone that made the subject more popular. In 2011, Buckl and Schweda [3] provided a detailed and, at the time of publishing, comprehensive review on EA, which focusses on EA frameworks and how they compare to one another. In contrast, Aier et al. [8] present a more condensed view on the subject, with a focus on comparing academic and practitioner views. They conclude that at the time, there was substantial potential in applying academic advances of EA in practice to better apply and manage EA in organisations.

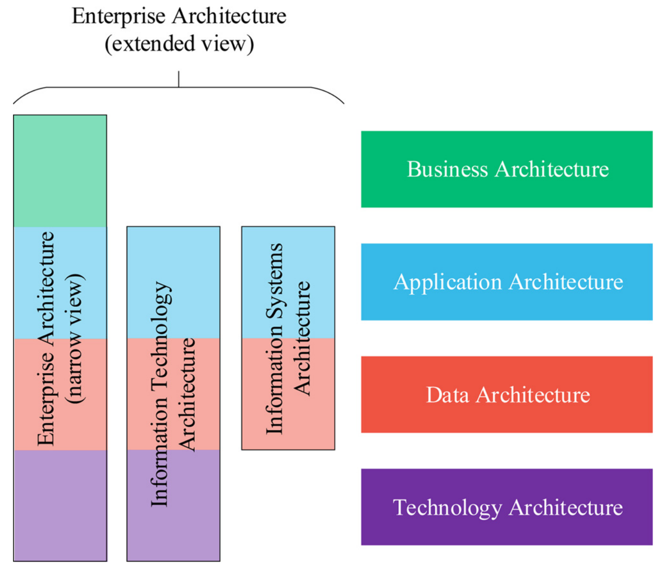


**Fig. 2.** EA definition, narrow and extended views.

In addition to the work that addresses the discipline as a whole, various state-of-the-art reviews are available that focus on specific aspects of EA: Niemi [7] focusses on the benefits of EA in the literature and in practice. He categorises and analyses the benefits that can be realized from EA in organizations. Stelzer [9] considers EA principles in closer detail and evaluates how they have been addressed in scientific publications. Stelzer indicates that neither an accepted definition for EA principles nor a conceptual framework for describing and formalizing EA principles is available. A review of critical issues that affect the EA process is provided by Lucke et al. [10]. Lucke et al. also present a categorization model with three levels for the issues that are identified in their review. Additional publications offer reviews on various aspects of EA: Andersen and Carugati [11] review EA evaluation and identify a lack of empirical studies and holistic views in this subdomain. EA implementation methodologies are described by Rouhani et al. [12], who identify research gaps in this area in modelling, management and maintenance. EA analysis, in combination with network thinking, is reviewed by Santana et al. [13], who summarize an extensive set of measures for EA assessment.

Saint-Louis and Lapalme [14] have recently published a systematic mapping study on EA that addresses the current diverse perspectives on EA. They provide an in-depth analysis of approximately 200 publications. Their findings support our extended approach and no major contradictions to our results have been reported. We hereby provide a view beyond the horizon of enterprise architecture by analysing approximately 4000 journal articles and conference proceedings. Our study reveals additional findings about the diversity of the discipline that have not been mentioned in earlier EA reviews.

### 2.3. Text mining as a part of artificial intelligence work

Text mining or text analytics is regarded as a subcategory of natural language programming (NLP), which is one of the founding branches of artificial intelligence [22]. Text mining methods offer a wide range of possibilities when ‘big data’ sources need to be analysed [23]. Various publications demonstrate the advantages of using statistical methods to derive models and analyse large quantities of data in short periods of time [24–26]. For the review that is described in this paper, there were several thousand scientific papers to be analysed and it would have required an immense effort to read and classify these documents manually [27].

There are several papers that deal with a generic approach for analysing data in which the text is not semantically decoded [25, 26]. Sebastiani [28] explains that automated text categorization can be used to work more efficiently in a similar example of analysing scientific literature. He also describes the information retrieval process, where data are collected and the set of documents – the so-called corpus – is derived. In general, two different approaches are described in the literature [24,29]:

1. Supervised Learning
2. Unsupervised Learning

In the supervised learning approach, the human teaches the model to the computer. Supervised learning hereby means learning with strong guidance and moderation by the researcher. The computer is used to accomplish several tasks "on its own", but the interaction with humans is quite intensive. The supervised learning method requires human interaction and is highly repetitive.

Due to grammar and spelling rules, proximity and truncation operators need to be used to extract terms in specified distances or patterns. The terms *cloud* and *computing* might appear in a document, for example. However, it seems to be essential to find both terms adjacent to each other to interpret them as *cloud computing*. Since *computing in the cloud* has the same meaning, a proximity rule may interpret *cloud* and *computing* within a distance of four words as the term *cloud computing* (e.g., cloud NEAR/4 computing). The correct distance needs to be refined by further testing and by checking the precision/recall ratio within the test set. The syntax depends on the tool and the required programming language. In most search engines, these proximity operators can be used to search for relevant information to build up the corpus precisely [23].

Usually, the proximity functions are defined as simple rulesets, e.g., the distance between 'Term 1′ and 'Term 2′ in a document [30]. Such search queries can be made more flexible by combining distance operators with wildcards or truncation operations. For example, *word**, with the right-side truncation, represents both *word* and *words* because * can be replaced by zero, one or a variable number of characters [31]. Truncation operators can be set on the right or left side of a word or in between characters. Supervised clustering is a classification method that is based on a given taxonomy. A taxonomy is hereby defined as a hierarchical description of terms and their relations, such that documents can be scored if they satisfy the specified rules [32]. A hierarchical taxonomy is derived manually from a sample set of documents and often based on a defined target label. Therefore, the target label must be defined first. The human supervisor suggests clusters or topics and annotates these by identifying descriptive terms for scoring the documents. Once hierarchical clustering has been completed, it can be applied to the corpus to score the documents. The highest-scoring topic may be classified as a category.

The unique characteristic of the unsupervised learning approach is that no human interaction is required and the computer derives rules "on its own". Pattern recognition and cluster detection, for example, suggest semantic relationships that may not have been known to the researcher upfront. Therefore, an unsupervised learning approach is likely to be effective when applied to large data sources [33]. In general, unstructured or semi-structured big data sources may be analysed efficiently by text mining procedures [25].

To detect patterns and structures, statistical methods may be used. Unsupervised learning means that the text mining algorithm detects patterns in the document pool – the corpus. All documents are processed separately to detect patterns. To identify terms that are present in all documents with equal frequency, the entropy function can be applied to derive the term weight. If term $i$ is given, entropy is calculated in document $j$. $d_i$ is the number of documents that contain term $i$ and $n$ is the total number of documents in the corpus.

$$entropy_i = 1 + \sum_{j=1}^{d_i} \frac{p_{ij} log_2 \left(p_{ij}\right)}{log_x(n)} \quad (1)$$

This function demonstrates the occurrence of a specific term within a defined set of documents. It is used to identify terms that are important in all documents because they are evenly spread [34]. To identify terms that describe document groups, a different function must be used. For example, the inverse document frequency can be used, which equals the number of documents in corpus $n$ divided by the number of documents $d_i$ where the term occurs. The more frequently a term appears in a group of documents, the more important it is [35].

$$IDF_i = 1 + log_2(\frac{n}{d_i}) \quad (2)$$

Clusters can be identified by using clustering algorithms such as k-means or guessing the number of clusters and centres. The clusters can be identified by their most descriptive terms, which can be interpreted to derive a "friendly" name for each cluster [36]. To identify the optimal value of k, the best splitting criteria can be calculated. The Davies-Bouldin Index is used to quantify the quality of a clustering algorithm.

$$DB = \frac{1}{N}\sum_{i=1}^{N} D_i \quad (3)$$

This method allows k, which is the number of cluster centres, to be optimized. It is often used to automatically detect clusters, which are interpreted as topics. There are several steps in determining the sharpness of clusters, which refers to the tightness inside clusters [37]. These unsupervised learning methods are widely used to discover new patterns and are applied throughout the analysis that is presented in the subsequent sections.

## 3. Applying text mining to enterprise architecture research

Fettke [38] suggests a classification scheme for literature reviews and applies it to multiple examples in the area of business informatics. To investigate how the text-mining-based approach compares to traditional literature review approaches, we have classified our work according to Fettke's classification scheme. The results are depicted in Table 1 and the classification results of our review are marked in green.

The major difference between our approach and other manual literature review approaches is reflected in Fettke's attribute *type*. All business informatics literature reviews that were investigated by Fettke are based on *natural language*, which means that the reviewers read and interpret the content of publications. Fettke's second option for *type* is *mathematical-statistical*. This type of review is not reflected in the reviews that were investigated by Fettke. However, he considers his own work to be *mathematical-statistical*. Our text-mining-based literature review approach can be considered a combination of both the types that were suggested by Fettke. We apply Natural Language Processing [22] to deduce statistical data from natural language, which can later be analysed using mathematical methods.

**Table 1**
Classification of our review according to Fettke's classification scheme [38] (For interpretation of the references to colour in this table, the reader is referred to the web version of this article).

| Review Characteristic | | Classification Results (those of our work are marked in green) | | | |
|---|---|---|---|---|---|
| Type | | natural language | | mathematical-statistical | |
| Focus | | research results | research method | theory | experience |
| Target | Formulation | not explicit | | explicit | |
| | Content | integration | criticism | central topics | |
| Perspective | | neutral | | position | |
| Literature | Selection | not explicit | | explicit | |
| | Extensiveness | foundations | representative | selective | complete |
| Structure | | historical | thematically | methodical | |
| Target Group | | common public | practitioners | common research | specialized researcher |
| Future Research | | not explicit | | explicit | |

Given the confirmation that there is a significant difference between our approach and manual literature review approaches in business informatics in terms of the manner in which the analysis is conducted, we suggest a process model for guiding our research methodology, which is presented in the next subsection and applied throughout this work.

### 3.1. Text mining process model for literature reviews

In the late 1990s, researchers first started to apply text mining to support their literature reviews. The approach was especially popular in the areas of medicine and biology [39] when it was first introduced. Today, text mining technologies are more commonly used to support systematic reviews across various research areas. However, they are not yet fully established in practice [40].

The methodology that is applied in this work leverages the knowledge that was obtained from previous studies that use text mining to support systematic reviews: Felizardo et al. [41] describe an approach that combines classical methods for the initial phases of a review with text mining support for the later stages. Thomas et al. [40] describe how the search and analysis phase of a literature review can be supported by text mining. Therefore, we combine classical literature review methodologies [42] with state-of-the-art text mining approaches [25] into a process model, which we used for the analysis that is described in this paper.

Chapman et al. [43] introduce a generic approach for text mining, which is called the CRISP-DM model. The CRISP-DM model identifies the business understanding as the initial starting point. Clearly defined research questions are the basis for data understanding, which complements the selection process. The following steps comprise the data preparation and modelling phase. These repetitive steps improve the results in each iteration. The results later lead to evaluation and deployment in business practise or back to the business understanding to adjust the input variables until the results meet the requirements.

For our process model, we leverage the iterative text mining practices of the CRSIP-DM model and derive the methodology that is presented in Fig. 3.

First, after the alignment of objectives, we begin the review activities at stage *'Review Initiation'*. Based on the objectives and focus points, we discuss the research. When the goals, research questions and scope are fixed, we can start the information retrieval process at stage *'Search for Publications'*. Once the selection of the proper corpus of documents has been completed, we start the iterative text mining process.

The iterative part starts with planning the iteration, which includes setting the goal of the current analysis and choosing relevant text-mining methods, which pre-defines how subsequent steps such data preparation will need to be executed, i.e., in which format data will need to be pre-processed. Afterwards, we adjust and transform the data pool accordingly. In the third phase, we conduct the analysis. Finally, in the fourth phase, we interpret the results and decide whether the goals have been achieved or further iteration processes are required.

After the results have been evaluated, the interpretation begins. Subsequently, it needs to be verified that the results that have been obtained correctly address the previously defined review

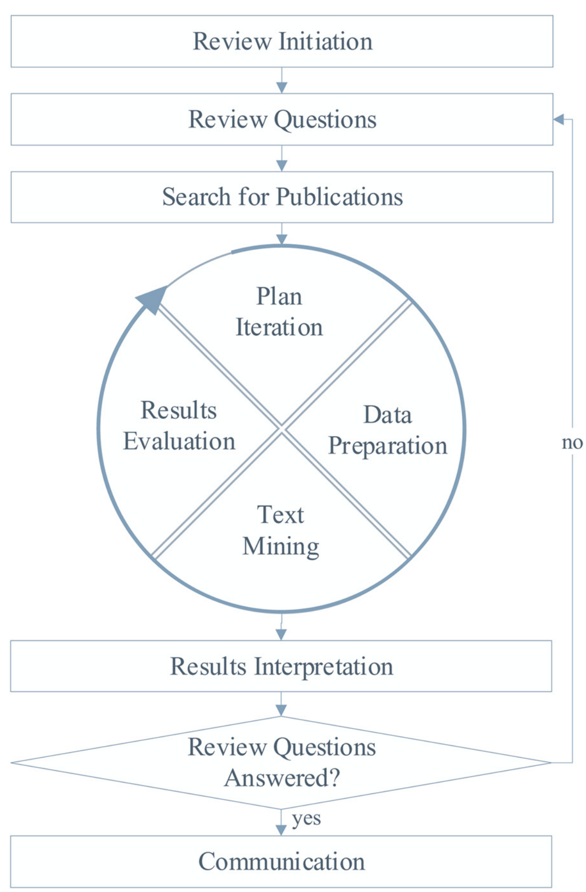


**Fig. 3.** Process model for applying text mining in systematic reviews.

questions. If this is not the case, it is necessary to repeat the process. Consequently, the review questions and the search for publications should be assessed and potentially adjusted, which likely requires another text mining iteration as well. If the review questions are finally correctly addressed, the results are visualized and prepared for publication in an appropriate way for the audience at the last stage, namely, '*Communication*'.

This process model has been applied throughout the entire review that is presented in this publication. Based on our experience, this process model has the potential to be applicable for similar studies in various fields. However, it is open for further research and studies are ongoing within our institute.

### *3.2. Information retrieval: publication search and selection process*

We searched for scientific publications in multiple relevant databases. We consolidated the results, applied a selection process to include only publications that are relevant for the work that is described in this article and excluded data items that could corrupt the results of our analysis, such as duplicate publications.

Our text mining analysis is based on the titles, abstracts and tags of the publications. We deliberately chose not to analyse the full texts of the publications. Schuemie et al. [44] show that the information density is highest in the abstract compared to other sections of a publication. Moreover, our approach enables us to avoid two issues: First, the linguistic specifics of abstracts and full texts are different and would require separate analytical methods [45]. Second, copyright, licensing and lawful access to scientific full-text content for text mining is difficult [46], especially since we want to combine records from multiple sources. Finally, due to the purpose and scope of our analysis, namely, categorization, topic identification and trend analysis, we decided that the information that is contained in title, abstract and tags is sufficient for our current work.

To retrieve relevant publications, the following databases were queried on November 1st, 2016:

- IEEE Xplore (http://www.ieee.org/web/publications/xplore/)
- Science Direct – Elsevier (http://www.elsevier.com)
- Springer Link (http://www.springerlink.com)
- Web of Science – Thomson Reuters (http://webofknowledge.com)
- ACM Guide to Computing Literature (http://dl.acm.org/)

For all databases, the following combined search string was used: *"enterprise architecture" OR "information systems architecture" OR "information technology architecture" OR "business-IT alignment"*. In recent years, the term "Enterprise Architecture" has been well-established and used throughout scientific and practitioner communities to identify the subject. However, especially in the early years of the discipline, other terms have been used, which explains why we extended our search string to include "information systems architecture" and "information technology architecture". EA was called "Information Systems Architecture" in its early years [1]. "Information Technology Architecture" is a part of EA, which is addressed individually in some cases [47] but also in the full context of EA. "Business-IT Alignment" is a closely related subject, which we consider to be part of EA. While EA considers all aspects of an organization together, the alignment between business and IT is a relevant part of this [3,48]. The inclusion of "Information Systems Architecture", "Information Technology Architecture" and "Business-IT Alignment" into our search string is in line with our extended view of EA, which is presented in Section 2.1.

The retrieved results from all databases have been exported and consolidated in BibTeX format. The information of the individual results is validated and completed using the Digital Object Identifier (DOI) lookup.

Once the consolidated results from various literature databases were available, a selection process that was based on inclusion and exclusion criteria was performed. We included English-language peer-reviewed publications of type Conference Proceedings and Journal Articles that are related to the subject Enterprise Architecture. We only included those that were published in or after 1987 since it is commonly regarded as the year in which EA became popular with Zachman's publication on EA [1]. We excluded any publication that was not written in English since the clear majority of publications are in English and other languages would need to be treated as separate data sets in the text mining analysis. In addition, we excluded duplicates and records without abstracts since the abstract is needed for the text mining analysis.

Based on the inclusion and exclusion criteria, the following selection process is applied; see also Fig. 4:

1. Consolidate results from all selected sources
2. Exclude by item type, language and publication date
   a Exclude any item that is not of type Conference Proceeding or Journal Article
   b Exclude any item that is not in English
   c Exclude any item that was not published after 1987
3. Exclude duplicates and announcements
   a Exclude duplicate studies
   b Exclude items that contain no actual research results (such as announcements of an issue)

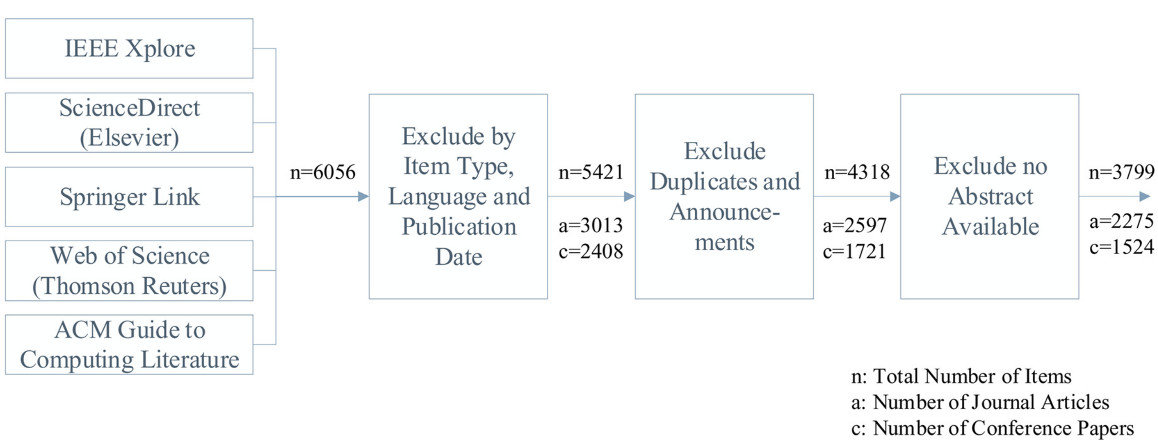


**Fig. 4.** Publication search and selection process.

4. Exclude items with no abstract available
   a Exclude any items for which no abstract is available

Finally, we selected 3799 records as input data for our text mining analysis. We manually reviewed 10% randomly selected publications to ensure that our data corpus resembles articles that are compliant with our extended view on enterprise architecture, as described in Section 2. To further validate our extended view of enterprise architecture, we split the dataset into two clusters – one that is compliant with the narrow view of EA (1517 publications; 40% of the corpus), which we call "narrow EA", and one that consists of the remaining data, which we call from "not-narrow EA". To confirm that the contents of clusters narrow EA and not-narrow EA are in line with our proposed EA terminology, we performed a clustering analysis based on maximum entropy classifiers. It is confirmed that the articles that do not specifically mention EA are driven by the following descriptive terms: "Information Systems Architecture", "Information System Architecture" and "Information Technology Architecture". These preliminary analytical results support our extended text-mining-based approach since 1) the number of articles that specifically mention EA is sufficiently high to justify an automated review and 2) the articles that do not specifically mention EA can be considered as part of an extended EA and hence serve as a basis for our objective of providing a view beyond the horizon.

The dataset, especially the distribution of publications throughout the years, can be used as first observations about the history of EA and the scientific relevance of the topic; see Fig. 1. From 1987 to 2015, the number of peer-reviewed publications on EA increased by 21% per year on average. In comparison, the total number of scientific publications has grown by approximately 3% per year on average [49], while the number of IT publications has grown by approximately 5%.[1] Therefore, we conclude that EA has remained a topic of interest since it was first introduced in 1987. Moreover, the scientific interest in EA has grown significantly more than that in IT overall.

## 4. History of research on enterprise architecture

### 4.1. Taxonomy for enterprise architecture research

As an additional input to our work, we refer to the existing EA literature reviews, which have been discussed in Section 2 of this article [3,7–13].

We used existing reviews to derive a taxonomy with two categorization hierarchies for structuring the whole topic of EA. The taxonomy is used as part of our analysis to classify available publications and analyse changes over the past years. We define the following main categories of EA research:

- *EA Understanding* refers to architectural content and how it can be represented. Key concepts of this subcategory are the definition of architectural building blocks, their interdependencies, views and viewpoints, and reference architectures.
- *EA Modelling* refers to the creation and management of architectural models. Key concepts of this subcategory are EA modelling languages, modelling tools that support the creation of EA models, modelling concepts and modelling deliverables.
- *EA Management* refers to how EA as a discipline is applied and managed. Key concepts of this subcategory are the development and implementation of architectures, their lifecycles, EA governance and the development of EA competency.

For each of the three main categories, we identify four subcategories; see Fig. 5 below. To evaluate the applicability of our taxonomy, we use the tag data that are available from the EA publications that we have collected. We identify each tag that is used in more than 20 documents of our data set and assign it to the matching subcategory. This validates the relevance of each subcategory by confirming that there are related data within our dataset.

Another reference for structuring the topic of EA is the structure of the EA framework. Our taxonomy, which we derived from previous literature reviews, can be mapped to the structure of the TOGAF framework. Table 2 shows this mapping.

The TOGAF framework is not primarily focussed on EA Modelling. Our EA Modelling category encompasses significantly more than is described in "Part VI TOGAF Reference Models". For example, The Open Group, which is the owner of the TOGAF framework, maintains the EA Modelling language ArchiMate separately from the TOGAF framework. Research that is focussed on ArchiMate and other EA Modelling languages is considered part of our EA Modelling category.

### 4.2. Shift from enterprise architecture to enterprise architecture management

To conduct our analysis, we first manually categorized 10% of the records. This equates 380 EA publications, which are randomly selected from our consolidated dataset. We manually categorized the documents by reading them and assigning them to the most suitable category in our taxonomy. These manually categorized records serve as test and training data sets within the text mining analysis.

We applied both an unsupervised and a supervised learning approach using software products SAS Content Categorization Studio[2] and Rapidminer.[3] As an input for the text mining processor, we supplied the title, tags and abstract of the publication. Unsupervised learning did not yield acceptable results, which is reflected in high classification errors (>40%). This is because automatically selected categorization terms are not meaningful from a content perspective but rather related to linguistic differences among texts that were written in different years – in our case, over 30 years. These deficiencies of unsupervised learning can be addressed with a supervised approach that includes human interaction, which is why we selected this method for our first research question. The graph in Fig. 6 shows the results of our analysis.

From the analysis results, it is evident that in the first years after the introduction of EA, publications focussed on EA Understanding. This is reasonable since it was important to first understand how various concepts such as EA building blocks and their dependencies needed to be defined. In recent years, the focus has shifted from EA Understanding to EA Management. This is also reflected in the discussion of "Enterprise Architecture Management" (EAM) instead of solely "Enterprise Architecture" (EA) in many publications. Various challenges in today's EA are not related to the definition of EA and its parts but to how EA can be successfully applied and managed in the context of organisations to deliver value. These types of challenges are addressed in the papers that focus on EA Management; see, for example, Foorthuis et al. [50]. The shift within the discipline from EA Understanding to EA Management is also described by Lankhorst [51] and Steenbergen [48]. The results of our analysis confirm their statements based on our comprehensive data set.

[1] Based on a query of Web of Science for IT publications on 14.03.2017 [83].

[2] http://support.sas.com/software/products/ccs/.

[3] https://rapidminer.com/.

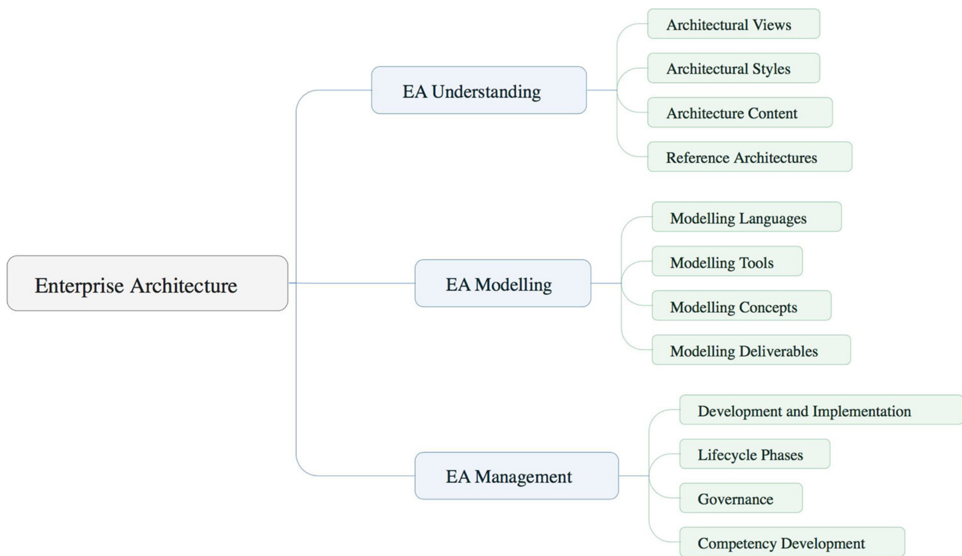


**Fig. 5.** Taxonomy for EA research.

**Table 2**
Mapping of our EA taxonomy to the TOGAF framework.

| Taxonomy Subcategory | Related TOGAF Parts |
|---|---|
| EA Understanding | Part IV Architecture Content Framework |
| | Part V Enterprise Continuum & Tools |
| EA Modelling | Part VI TOGAF Reference Models |
| EA Management | Part II Architecture Development Method |
| | Part III ADM Guidelines and Techniques |
| | Part VII Architecture Capability Framework |

Nevertheless, a significant number of current publications are focussed on EA Understanding and address challenges that are related to the plurality of definitions of EA, which, to a certain extent, still exist today. Lapalme [16] reviews the different schools of thought regarding EA in a recent publication.

According to our analysis, EA Modelling has continuously remained the topic of publications on EA, but significantly fewer publications than EA Understanding and EA Management. However, the share of publications on EA Modelling has not declined over time, as assumed by Steenbergeben [48]. This category of EA research is still relevant today, which is reflected in the work that is done on recently proposed EA modelling language ArchiMate, for example. In addition, the current general trends of analytics and artificial intelligence foster the recent interest in EA Modelling. Several current studies address the machine readability of EA models to assess them automatically and derive relevant information for decision making; see, for example, Hinkelmann et al. [52].

## 5. Current and future enterprise architecture research trends

To identify and analyse current EA trend topics, we applied an approach that combines supervised and unsupervised learning. First, we used a partly supervised topic identification method to identify trends. In a second step, we run a fully unsupervised clustering analysis to assess the context of the identified trends. The results of both steps are used to investigate the trends with the strongest impact in closer detail. In the analysis, we compared our results to those of other authors, including the results of the Gartner Hype Cycle.

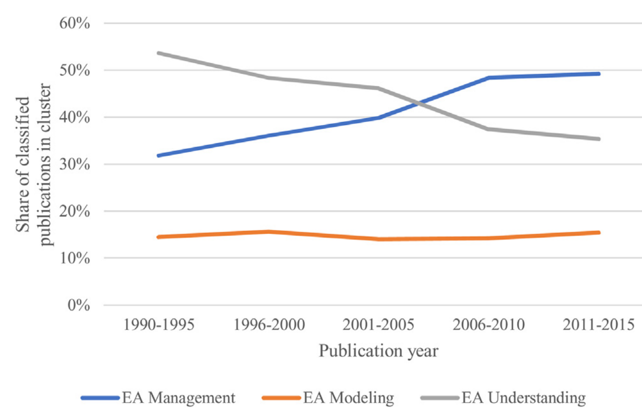


**Fig. 6.** History of EA research focus.

### 5.1. Identifying, measuring and forecasting current EA trends

For the partly supervised topic identification, we use two software products: SAS Content Categorization Studio[4] and R.[5] The data set was separated into two groups: documents that were published recently (2015–2016) and documents that were published earlier (2002–2014). We excluded publications from before 2002 since this part of the analysis focusses on current trends. Therefore, we neglect documents that were published more than 15 years ago. First, characteristic terms that distinguish recent from earlier documents are identified for the analysis using maximum entropy classifiers; for details on the method, see Section 2.3. This resulted in the following list of terms: *adapt, agenda, agile, big data, cloud, complexity theory, consensus, consumer, cyber, distribution, entrepreneurial, message, objectives, preliminary, publishing, quickly, similarity, smart, statistical, sustainable, things.* In a second analysis step, we manually reviewed the resulting terms and related documents to identify relevant subjects in terms of content. Terms that could not be mapped to

[4] http://support.sas.com/software/products/ccs/.
[5] https://www.r-project.org/.

**Table 3**
Characteristic terms of recent EA publications and identified trends.

| Identified Term | Related Subject/Trend |
|---|---|
| cloud | Cloud Computing and Enterprise Architecture |
| complexity theory | Complexity Theory and Enterprise Architecture |
| agile OR adapt | Agile or Adaptive Enterprise Architecture |
| big data | Big Data and Enterprise Architecture |
| things | Internet of Things (IoT) and Enterprise Architecture |
| entrepreneurial | Entrepreneurship and Enterprise Architecture |
| smart | Smart Machines and Enterprise Architecture |
| sustainable | Sustainability and Enterprise Architecture |

**Table 4**
Distribution of Trends that are Related to Articles in Clusters "narrow EA" and "not-narrow EA".

| | Number of Publications Related to Trend | | |
|---|---|---|---|
| Trend | Total | Narrow EA | Not-Narrow EA |
| Agile/Adaptive | 180 | 90 (50%) | 90 (50%) |
| Cloud Computing | 161 | 66 (41%) | 95 (59%) |
| Big Data | 39 | 14 (36%) | 25 (64%) |
| Complexity Theory | 17 | 16 (94%) | 1 (6%) |
| Entrepreneurship | 50 | 7 (14%) | 43 (86%) |
| Smart Machines | 61 | 17 (28%) | 44 (72%) |
| Sustainability | 117 | 36 (31%) | 81 (69%) |
| IoT | 29 | 7 (24%) | 22 (76%) |

a subject have been excluded from the subsequent analysis. Table 3 shows the results.

Over time, we considered the number of documents that were related to each of the identified trends relative to the total number of publications of a given year. In addition to evaluating the past development of the identified trends, we obtained a prognosis up to 2020 using an Auto ARIMA Model. The results are depicted in Fig. 7. According to our forecast, Cloud Computing is and will remain the trend with the strongest impact on scientific EA publications. The trend with the strongest growth in impact, according to the forecast, is Internet of Things (IoT).

To better understand the relationships of EA with the identified trends, we also investigated the extent to which these trends appear in the clusters "narrow EA" or "not-narrow EA", which are described in Section 3.2. According to Table 4, six trends are significantly present in each cluster with minor quantitative differences. Entrepreneurship is significantly present only in the "not-narrow EA" cluster, complexity theory is almost exclusively present in the "narrow EA" cluster, and all other trends are present in both clusters.

## 5.2. Understanding the context of current EA trends

To better understand the context of the identified trends, we used an unsupervised clustering analysis approach for topic detection. Text mining software RapidMiner[6] was used for this part of the analysis. We referred to the same corpus as in the previous analysis step, which focusses on the publications from 2002 to 2016.

The idea was to split the documents into timely hierarchical groups and identify clusters in each document group. Comparing the clusters and their descriptive terms provides an impression of how the discipline EA has developed over time. For details on the applied text mining techniques, refer to Section 2.3 of this work.

The Davies-Bouldin Index indicates how precisely cluster centres differ from one another. Therefore, it offers a good measure for optimizing the number of clusters. We calculated the optimized Davies-Bouldin Index for 0–20 cluster centres. The documents were split in 3 corpuses: A) 2002–2006, B) 2007–2011, and C) 2012–2016. The optimal number of clusters was derived from the Davies-Bouldin Index of each document group. The lowest average index was attained with seven clusters. Based on this optimisation of the number of clusters, the 10 most important descriptive terms were identified. This was done for seven clusters in each document group. Table 5 shows the results. Afterwards, the descriptive terms were compared to determine whether and how the clusters changed over time.

Only some topics are present in multiple document sets. It is noteworthy that the topic "Healthcare" is present in all periods (see clusters A7, B5, and C7). Healthcare is also identified as a topic in similar clustering analyses for other IT-related research areas [53, 54]. This is presumably because healthcare-related publications include distinctive language that distinguishes them from other publications. When examining the individual papers of the healthcare clusters, we observe that these are, for example, case studies or specific reference models for the medical sector. The same observation can be made for another application area of EA – "Manufacturing". It is represented in clusters A3, B2, and C2. Based on these observations and given the previously identified trends regarding EA and Entrepreneurship, we decided to examine more closely EA application areas; see the results in Section 5.3.7.

Many additional observations can be made from the results of the unsupervised clustering analysis. However, these observations often raise various questions when considered separately. Therefore, we do not rely only on this part of the analysis. Instead, we combine it with findings that were presented earlier. Thus, a comprehensive view of EA trends can be obtained.

## 5.3. Closer look at individual EA trends

In the next step of our analysis, we combined the results of the partially supervised topic identification with the observations of the clustering analysis to investigate various trends in a broader context. Each trend is considered in one of the following subsections.

In addition, we cross-check our findings with the results of the Gartner Hype Cycle for Enterprise Architecture, which is available for the years 2010 to 2017 [55]. The Gartner Hype Cycle is a structured, qualitative analytical tool for trend analysis, which is based on surveys and expert judgement [56]. Although Gartner's research has a dominant position in practice, it has received limited attention from academics so far [57,58]. We want to understand the relationship of our results, which are derived from academic sources, with EA in practice. Therefore, we refer to the Hype Cycle. Moreover, from our point of view, the comparison of our results with those from the Gartner Hype Cycle provides interesting insights since they are obtained using different methodologies and have different focusses but are related to the same subject (see the comparison in Table 6).

### 5.3.1. Cloud computing and enterprise architecture

According to our analysis, Cloud Computing [59] is currently and will continue to be until 2020 the trend with the strongest impact on scientific EA publications. This is plausible since it has changed the way we design, build, operate and consume services. Therefore, it has a major impact on all layers of Enterprise Architecture [60].

The relevance of the Cloud Computing trend for Enterprise Architecture is not restricted to the scientific space. It can be confirmed for practitioners, as well by considering the Gartner Hype Cycle. Cloud Computing is present in the Hype Cycle from 2011 and is considered a strong trend ("At the Peak" within the Hype Cycle) up to 2016. In 2017, Cloud Computing is first ranked as

[6] https://rapidminer.com/.

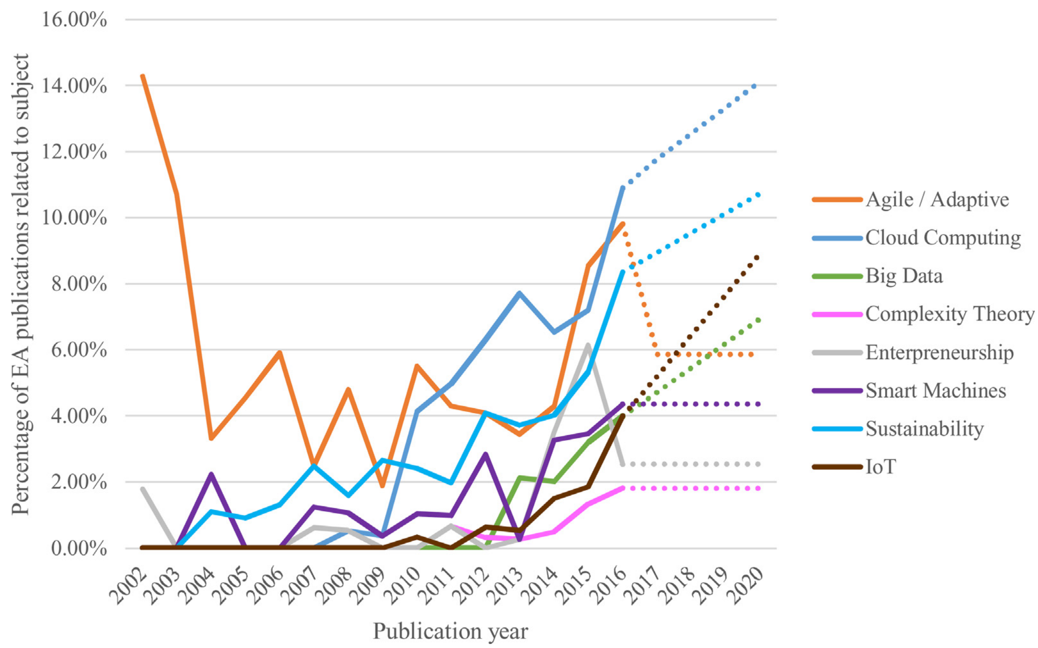


**Fig. 7.** History and forecast of current research trends in the scientific EA literature.

**Table 5**
Clustering results with related terms from unsupervised analysis.

| Cluster Name | Publication Year-Group | Terms | Number of Documents |
|---|---|---|---|
| A1 | 2002–2006 | alignment, zachman, knowledge, supply, chain, strategic, life, strategy, component, diagrams | 85 |
| A2 | 2002–2006 | security, government, access, agencies, federal, adaptive, sharing, local, risk, records | 57 |
| A3 | 2002–2006 | manufacturing, virtual, agent, backslash, control, coordination, automation, interoperability, product, distributed | 82 |
| A4 | 2002–2006 | object, governance, domain, oriented, principles, distributed, driven, workflow, middleware, core | 37 |
| A5 | 2002–2006 | implementation, papers, factors, companies, success, planning, agility, survey, review, directions | 55 |
| A6 | 2002–2006 | architectures, software, architectural, languages, language, description, integration, evaluation, change, computer | 88 |
| A7 | 2002–2006 | health, care, medical, informatics, clinical, mobile, patient, record, hospital, services | 60 |
| B1 | 2007–2011 | oriented, software, services, engineering, driven, patterns, requirements, zachman, architectures, integration | 245 |
| B2 | 2007–2011 | ontology, semantic, knowledge, supply, chain, ontologies, mining, domain, manufacturing, artificial | 123 |
| B3 | 2007–2011 | method, quality, assessment, algorithm, measurement, force, phase, accuracy, evaluation, metrics | 123 |
| B4 | 2007–2011 | decision, change, metamodel, learning, making, archimate, influence, project, performance, portfolio | 287 |
| B5 | 2007–2011 | security, health, computing, healthcare, cloud, network, access, grid, care, medical | 215 |
| B6 | 2007–2011 | alignment, maturity, strategic, strategy, principles, strategies, governance, aligning, organization, organisations | 129 |
| B7 | 2007–2011 | government, interoperability, digital, agencies, local, governance, governments, administration, national, electronic | 82 |
| C1 | 2012–2016 | cloud, computing, services, outsourcing, architectures, oriented, providers, privacy, resources, applications | 99 |
| C2 | 2012–2016 | manufacturing, smart, networks, network, interoperability, supply, energy, chain, product, sustainable | 207 |
| C3 | 2012–2016 | government, factors, governance, innovation, decision, sector, success, making, literature, studies | 387 |
| C4 | 2012–2016 | software, engineering, requirements, quality, pattern, project, method, methodology, architectural, agile | 516 |
| C5 | 2012–2016 | security, cyber, secure, physical, risk, access, control, privacy, scheme, risks | 85 |
| C6 | 2012–2016 | alignment, maturity, strategic, strategy, organisations, organization, aligning, aligned, method, evaluation | 192 |
| C7 | 2012–2016 | ontology, social, health, semantic, knowledge, archimate, healthcare, ontologies, semantics, medical | 254 |

"Sliding Into the Trough". The trend is entirely missing from Gartner's EA hype cycles before 2011, while scientific publications had already identified it in 2008. In 2010, 4.14% of scientific EA publications addressed Cloud Computing.

The findings of our clustering analysis demonstrate that "security" and "privacy" are closely related to EA Cloud Computing. In general, security and privacy are prominent topics in Cloud Computing because services are commonly consumed via the public internet, which allows traffic to be intercepted [61]. Moreover, the typical storage of cloud service data at the provider's

**Table 6**
Comparison of our trend analysis with the Gartner Hype Cycle.

| | Our Trend Analysis | Gartner Hype Cycle for EA |
|---|---|---|
| Methodology | Data Analysis | Surveys and Expert Judgement |
| Focus | Scientific | Industry |
| Subject | Enterprise Architecture | Enterprise Architecture |

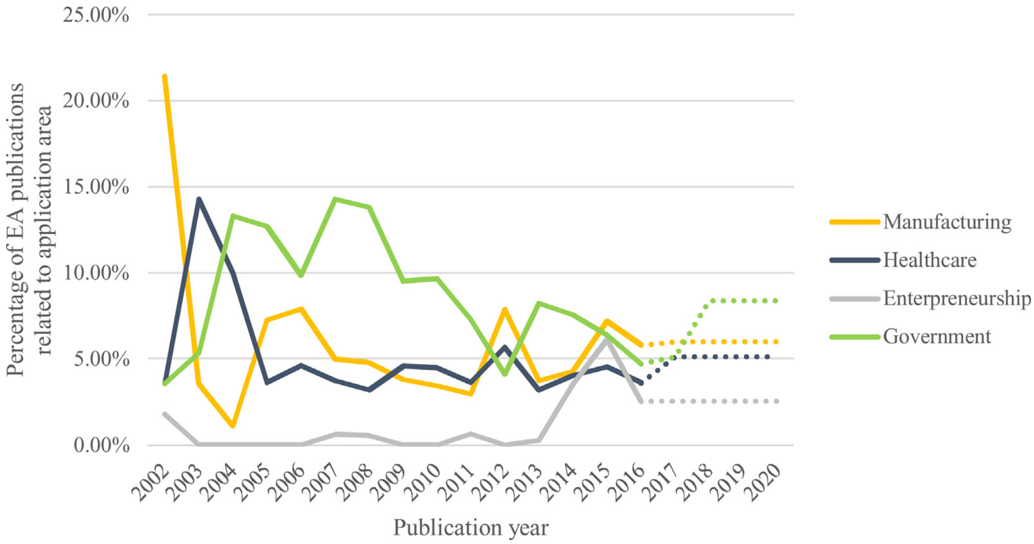


**Fig. 8.** History and forecast of EA application areas in the scientific EA literature.

site, rather than the consumer's, presents a challenge due to data privacy regulations, especially in international setups. Enterprise Architecture can help address these challenges of Cloud Computing in a systematic, vendor-neutral way [62].

*5.3.2. Adaptive or agile enterprise architecture*

Another trend that appears to be prominent proposes a reconceptualization of EA so that the discipline and the resulting architectures are more adaptive to changes [63]. The trend is driven by the increasing pace of change in and the convergence of both business and IT [2]. Different authors and publications refer to the topic as either Adaptive [63,64] or Agile EA [65].

Considering the results of our trend analysis, it is noteworthy that this trend has already received significant attention since 2002 and has been addressed continuously throughout recent years. In 2015 and 2016, there was an additional spike in the share of EA publications that address the subject. Earlier papers address the subject for the manufacturing industry in the context of “agile manufacturing” and “virtual enterprise”, which were popular in 2002 [66,67]. More recent publications address the topic not only for the manufacturing industry but in a more general manner [52].

Adaptive Enterprise Architecture is considered in the Gartner Hype Cycle only once, in 2016. Gartner describes “Situationally Adaptive Behaviour” as an EA trend that is on the rise. However, in 2017, it is not mentioned anymore.

*5.3.3. Sustainability and enterprise architecture*

We find that the EA trend of Sustainability has clearly grown in importance. There is an increase in the number of EA publications that address sustainability over the last fifteen years, from zero documents in 2002 to more than 8% of the publications on EA in 2016.

Sustainable development is regarded as one of the grand challenges for our current society, which has the aims of increasing the wellbeing of present and future generations and protecting the planet from degradation by sustainably managing natural resources [68]. One view of Enterprise Architecture is the systems-in-environment perspective, which considers not only the architecture of an organisation but also how it interacts with its environment [16]. From this perspective, EA needs to address environmental concerns and how sustainable development can be achieved [2]. EA and its methodologies can be used to understand better the dependencies and implications of sustainable development; see, e.g., Villarreal [69] for an analytical framework.

In the publications that address sustainability and EA, we see a clear overlap between this trend and the trend regarding adaptive EA, which was presented earlier. It is concluded that an adaptive architecture is more sustainable since it can adapt to changing conditions rather than requiring a replacement [70].

The Gartner Hype Cycle for EA does not mention Sustainability. However, there is a separate Hype Cycle that focusses directly on sustainability. While there is an overlap between the trends in both Hype Cycles, no direct connection identified between EA and Sustainability.

*5.3.4. Smart machines and enterprise architecture*

Our analysis indicates that there is a trend regarding Smart Machines and Enterprise Architecture that is prominent in the most recent year of our analysis, namely, 2016. Approximately 4% of the EA publications address this subject. The term “Smart Machines” refers to machines that are supported by cognitive technologies and hence are able to support or even replace human labour [71].

By examining the individual EA publications more closely, two specific examples are identified: Smart City [72] and Smart Grid [73]. Introducing a Smart Machine and redesigning an existing system in a smart fashion are major transformation activities. Enterprise Architecture methodologies can be applied to support these transformations by considering both the business and the information systems views.

Neither Smart Machines nor artificial intelligence are addressed in the Gartner Hype Cycle for Enterprise Architecture.

*5.3.5. Internet of things and enterprise architecture*

According to our analysis and forecast, the Internet of Things (IoT) is the EA trend for which we expect the strongest growth until 2020. The trend is represented significantly in the documents we analysed from 2012. IoT refers to physical devices that connect with one another and primarily communicate via the internet. Examples range from electronic health to connected cars and intelligent manufacturing, which is sometimes referred to as “industry 4.0” [74].

From an EA perspective, IoT means a massive increase in the diversity of architectural building blocks and corresponding integrations, which need to be managed. Due to these changing conditions, EA approaches and concepts such as meta-models need to be extended. However, EA methodologies can also help manage better the transformations that are related to the Internet of Things [75].

The Gartner Hype Cycle confirms our findings. IoT is represented in the Hype Cycle for EA from 2012 and considered to be at its peak in 2017.

*5.3.6. Big data and enterprise architecture*

Beginning in 2011, the general trend of Big Data has boomed and resulted in various scientific publications that address the subject [53]. In our analysis, we find that EA publications started addressing Big Data two years later, in 2013. There are two major streams of thought in the articles we have analysed:

1) EA can be applied to develop, implement and manage Big Data architectures to ensure alignment and value creation [76,77].
2) Big data methodologies can be applied to support enterprise architecture activities. Specifically, analytics and artificial intelligence technologies can be used to analyse and optimize architecture models [52].

Big Data is represented in the Gartner Hype Cycle for EA from 2012 until 2016. Hence, Gartner highlighted this trend one year before scientific publications addressed the subject. Interestingly, Gartner does not include Big Data or analytics in their 2017 Hype Cycle for EA. However, our trend forecast indicates that the topic will still receive significant attention until 2020.

*5.3.7. Entrepreneurship and enterprise architecture*

Our trend analysis indicates a trend regarding Entrepreneurship in scientific EA publications. From 2014, a significant share of the documents that we analysed refer to entrepreneurial settings, such as small and medium enterprises (SMEs) or even start-ups. SMEs often face several problems due to a lack of structure and oversight within the company. EA can be used as an extended setup to address these issues and ensure alignment [78]. Similar challenges apply to start-ups under slightly different conditions. Start-ups have the advantage that they are typically operating in a greenfield setting and therefore do not need to deal with the integration of legacy systems, which reduces complexity. At the same time, it is a challenge that activities in a start-up need to be pragmatic and effective. This applies to EA as well. Therefore, an EA approach for a start-up needs to be tailored to these conditions [79].

Our clustering analysis shows various past application areas of EA, including the manufacturing industry, healthcare and government. We analysed within our dataset how these traditional EA application areas compare to the use of EA in entrepreneurial settings. The results are depicted in Fig. 8. Before 2014, EA publications focussed on the traditional application areas, with government being the most popular. Since 2014, entrepreneurial settings have been addressed to a similar extent as traditional application areas in the publications that we analysed.

Entrepreneurship, SMEs and start-ups are not addressed in the Gartner Hype Cycle for Enterprise Architecture.

*5.3.8. Complexity theory and enterprise architecture*

From 2014, we find an increasingly prominent trend regarding Complexity Theory and Enterprise Architecture. Complexity Theory presents a framework for understanding based on concepts such as non-linear systems and network theory. It can be applied in various areas, including social sciences [80]. For EA, Complexity Theory can be applied to understand and model architectures and to measure attributes such as their complexity [81,82]. Moreover, findings and methods from Complexity Theory can be used to optimize given architectures. We identify a link to the trend of Big Data, which was presented earlier, since an architecture assessment and optimisation based on Complexity Theory likely require an analytics solution to perform the required computations.

Complexity Theory is not addressed in the Gartner Hype Cycle for Enterprise Architecture.

## 6. General discussion and conclusions

This publication presents the first comprehensive review of a large body of academic knowledge that has been created in the last 30 years on research on EA. Basing our analysis on this enormous dataset presents an advantage but also a limitation since we are not able to perform an in-depth analysis of individual articles. Therefore, we encourage readers who are interested in specific details or specific sub-domains of EA to refer to other more-focussed reviews, which are presented in Section 2.2. We regard our analysis as a “view beyond the horizon”, which means that we consider a wider variety of search terms at the initial stage of our review. We demonstrate that the large surplus that we found compared to many exiting literature reviews is significant with respect to enterprise architecture and confirms that it has become a highly dynamic discipline that is attracting growing scientific interest.

Our trend analysis provides strong guidance regarding the impact of topics such as sustainability, cloud computing, internet of things, smart machines and complexity theory on the discipline of EA. A major advantage of our approach compared to others is that we can quantify the impact of trends on a large scale and present forecasts. However, it has the following limitation: While the number of search query hits in articles and the additional outcomes of our learning studies appear to imply a measure of importance, our data analysis mainly considers a “statistical” prevalence at first sight. To validate our results, it is essential to apply “human intelligence”, namely, expert knowledge, by reading and discussing results. For example, the necessity of human intervention has been demonstrated by trying to interpret the results of the fully unsupervised clustering analysis via only statistical prevalence. A qualitative discussion can be found in Section 5 of this article. In addition, the article by Lapalme et al. [2] and the work of Romero and Vernadat [6] present additional related expert knowledge and therefore complement our trend analysis.

When comparing the results of our trend analysis with the Gartner Hype Cycle, which is especially popular with practitioners [58], we identify a clear difference between “conceptual” and “technology” trends. Table 7 provides a comparison between our analysis and the Gartner Hype Cycle in terms of the trends we have identified. It is striking that the Gartner Hype Cycle reflects only the technology trends that were identified by our analysis.

However, Gartner also identifies trends for EA, including conceptual ones, that are not identified in our trend analysis. “DevOps”, “Design Thinking”, “Customer Journey Analytics”, “Web-Scale Application Architecture”, “Workforce Planning and Modelling” and “IT/OT Architecture” are considered to be at their peaks in the 2016 Hype Cycle for EA and are not identified in our analysis. If we explicitly check for these topics in our data set, we find that they are not significantly represented.

**Table 7**
Comparison of results from our trend analysis with the Gartner Hype Cycle.

| | Our Trend Analysis | Gartner Hype Cycle |
|---|---|---|
| Cloud Computing | From 2010 to 2017 | From 2011 to 2017 |
| Complexity Theory | From 2014 to 2017 | N/A |
| Agile or Adaptive EA | From 2002 to 2017 | N/A |
| Big Data | From 2013 to 2017 | From 2012 to 2016 |
| Internet of Things | From 2012 to 2017 | From 2012 to 2017 |
| Entrepreneurship | From 2014 to 2017 | N/A |
| Smart Systems | From 2004 to 2017 | N/A |
| Sustainability | From 2004 to 2017 | N/A |

Based on the findings of our review, we suggest that further research on EA should be conducted in the following areas:

- Topics “DevOps”, “Design Thinking”, “Customer Journey Analytics”, “Web-Scale Application Architecture”, “Workforce Planning and Modelling” and “IT/OT Architecture” are identified by Gartner as practitioner EA trends with major publicity. These topics have not been considerably addressed in academic publications. Therefore, these areas certainly qualify for further investigation.
- The differences between the results of our analysis and those of the Gartner Hype Cycle are interesting observations and potential starting points for future research. These findings raise the question of whether there is a mismatch between academic EA work and EA in practice. Moreover, we think that in general −not restricted to the subject of EA − the relationship between Hype Cycles, such as the one from Gartner, and academic research presents an opportunity for further investigation.
- Our trend analysis revealed that multiple publications consider EA for specific industries, e.g., healthcare, manufacturing and government. Further research could investigate this observation in detail to better understand differences and similarities across different industries.
- The variety of trend term occurrences within the two clusters (narrow EA and not-narrow EA) requires further investigation, especially for trends Entrepreneurship and Complexity Theory.

In conclusion, we find that the discipline of EA has grown substantially over the last thirty years since it was first introduced. Nevertheless, it is still a young discipline, which offers great potential for researchers to contribute and grow the maturity of the discipline. This is reflected in the ever-growing number of publications on EA. The subject understanding of EA has evolved but we still observe misalignment within the EA community regarding the definition and scope of EA, as was also pointed out by Saint-Louis and Lapalme [14]. In addition, a significant current challenge is the successful application of EA in the context of organisations, which is reflected in the increasing number of publications that we found to be focussed on EA management as part of our taxonomy-based analysis.

Out trend analysis identifies various topics with impact on EA that will shape the discipline in the future. Hence, our results may provide a foundation for future studies and support authors during the selection of their research topics and questions.

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