A Systematic Literature Review of Big Data Literature for EA Evolution

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Abstract: Many organizations identified the opportunities of big data analytics to support the business with problem-specific insights through the exploitation of generated data. Socio-technical solutions are developed in big data projects to reach competitive advantage. Although these projects are aligned to specific business needs, common architectural challenges are not addressed in a comprehensive manner. Enterprise architecture management is a holistic approach to tackle the complex business and IT architecture. The transformation of an organization's EA is influenced by big data projects and their data-driven approach on all layers. To enable strategy-oriented development of the EA it is essential to synchronize these projects supported by EA management. In this paper, we conduct a systematic review of big data literature to analyze which requirements for the EA management discipline are proposed. Thereby, a broad overview about existing research is presented to facilitate a more detailed exploration and to foster the evolution of the EA management discipline.

Keywords: Enterprise Architecture, Enterprise Architecture Management, Big Data Management, Big Data Projects, EA Evolution

1 Introduction

As more and more data are created by internal information systems, social media platforms and Internet of Things (IoT) devices organizations identified the analysis of these data as a useful source of knowledge to optimize their business. Several challenges for data analytics, resulting from a new paradigm of data creation and new economic conditions, made particular technologies necessary. Big data analytics has become an important differentiating factor for many organizations in the last years. The management of organizational and data integration aspects are an essential success factor and preliminary stage for big data analytics. In the words of Bertino: "The analysis step itself is easy; preanalysis is the tricky part" [Be13]. Chen et al. see "no doubt that the future competitions in business productivity and technologies will surely converge into the big data explorations" [Ch13]. The problems of conventional technologies to cope with big data have created new technologies that address these problems. Chen et al. describe several high-impact applications of big data analytics such as e-commerce and market intelligence, e-government and politics 2.0, science and technology, smart health and well-being, and security and public safety [Ch13]. Hence, big data is a relevant topic

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for the private and public sector and influences our lives as citizens, employers, employees and customers [Ji15]. Big data projects describe initiatives with a strong focus on delivering socio-technical solutions mainly based on data storage, processing and analysis of big data. All these initiatives are based on the goal to gain new business insights and therefore have to be aligned with the business. Furthermore, big data projects create a huge amount of transformation processes that affect large parts of an enterprise's Enterprise Architecture (EA). Many organizations struggle with the integration of big data technologies into their existing business and IT architectures. This problem is described from different perspectives, but not explicitly connected to a comprehensive strategic management solution such as Enterprise Architecture Management (EA management). EA management is a commonly accepted method to support enterprises in their continuous transformation processes [La09], [Op09]. EA management provides a systematic approach to enhance transparency, to support business and IT-alignment and to enable the strategy-driven development of the Enterprise Architecture (EA) as a whole [Ha12]. On this basis EA management provides "architectural guidance for projects" [ARW08]. Based on created EA models stakeholders are supported in their planning tasks by conceptual views on the organization's EA [La09], [Op09]. EA management has to be adapted over time to cope with the complexity of the EA and to react to the aforementioned changing environment and new trends [Be12], [BS11]. One of these trends is big data analytics that creates new types of architectural challenges and requirements for EA management solutions. In this paper, we review big data literature to answer the following research questions:

RQ1: Which EA requirements do exist in the big data context?

RQ2: Which challenges in big data projects referring to EA management do exist?

RQ3: Are there approaches or methods in big data management considering EA management?

This systematic exploration comprises a first step towards the future evolution of the EA management discipline. Section 2 details the research design of the systematic literature review based on the guidelines provided by Kitchenham [Ki04]. The identification of relevant literature is described in Section 3. Section 4 presents the analysis and interpretation of the review results. The paper concludes with Section 5, which summarizes the research outcome and shows limitations of the conducted systematic literature review. Finally, indications for future research are proposed.

2 Research Design

Since new trends such as the analysis of big data creates new challenges for organizations and their EA management, new problems and gaps in current research may originate from these trends and their interference with existing management systems.

A literature review is a good instrument “to identify gaps in current research in order to suggest areas for further investigation” [Ki04]. Thus, a systematic literature review (SLR) in line with Kitchenham [Ki04] is applied to investigate these gaps that are of interest to foster the evolution of the EA management discipline. This SLR provides an overview about existing work. The research approach is based on secondary data, because secondary research data is available immediately and a large amount of experiences can be accessed covering a wider area of interest. According to Kitchenham, a SLR is composed of three main phases: planning the review, conducting the review, and reporting the review [Ki04]. The planning of the review includes the identification of the need for a review and the development of a review protocol. The rationale for this SLR is an exploration of the proposed lack of EA management support in big data transformation processes (cf. Section 1) and the objective to adapt EA management to the changing environment and new trends. The components of the review protocol are detailed in the following sections to ensure research rigor. We conduct the review in Section 3. Afterwards, the review is reported in Section 4, which incorporates the analysis and interpretation process to answer the underlying research questions presented in Section 1.

3 Literature Identification

The process of literature identification is described within this section. The guidelines of the systematic literature review provided by Kitchenham [Ki04] are used to structure the literature identification. Thus, literature sources (cf. Section 3.1) and the search and selection process (cf. Section 3.2) are described in detail.

3.1 Literature Sources

The first step of a systematic literature review is the definition of the literature sources. As far as a broad overview about existing research is pursued, the search is confined to the databases ACM digital library[4], IEEE Xplore[5], and Google Scholar[6]. The ACM digital library contains all ACM publications, including journals and conference proceedings. The Association for Computing Machinery (ACM) is the world's largest scientific and educational computing society and hence has a huge impact on research. The IEEE Xplore Digital Library contains more than 2 million conference publications and more than 1 million journals and magazines and includes the most highly cited publications in computer science. The number of journals and conference proceedings included confirms the IEEE Xplore Digital Library as an appropriate source for a broad analysis of existing research. Google Scholar is a web search engine for published research and includes most peer-reviewed online journals of Europe and America.

[4] http://dl.acm.org/
[5] http://ieeexplore.ieee.org/Xplore/home.jsp
[6] http://scholar.google.com/

Google Scholar ranks publications weighing the full text, author, citations and other meta data of documents. These sources are selected to generate a representative and up to date literature base that should lead to an unbiased indication of requirements described in big data literature. The literature base is not confined to specific constraints as far as the objective of the literature review is a first approximation of a large body of literature.

3.2 Search Process

The search process utilizes the defined literature sources to identify relevant literature following a defined structure. The search process consists of the following steps considering the guidelines of Kitchenham [Ki04]: Search criteria construction and manual selection process. The whole process is visualized in the flow diagram depicted in Fig. 1 and described in the following.

Search criteria construction. We designed specific search strings that are applied to the selected sources. These search strings are selected to cover relevant literature concerning (1) explicitly stated requirements in the big data context, (2) challenges in the big data context that allow a derivation of requirements, as well as (3) experiences in big data projects and big data management that lead to a set of requirements for EA management. Thereby, the following search strings are used for the full text search: “big data requirements”, “big data challenges”, “big data project” and “big data management”. Since the understanding of EA management differs depending on the research community, we decided to not use a dedicated term such as “EA management” in combination with the aforementioned search strings. This fact demands a manual selection task that is explicated in the subsequent manual selection process. The conducted search processes led to 193 results in the ACM digital library, 144 results in the IEEE Xplore Digital Library and 4370 results in Google Scholar. Because of the massive amount of literature published within the big data subject, further filter criteria are applied to consider economic aspects and the feasibility of the selection process [Ki04]. Hence, several constraints are applied to the process of literature identification. At first, only literature published between 2012 and the date of the literature review is analyzed. As far as big data is a fast moving discipline, this constraint is considered necessary to exclude obsolete requirements, challenges, and experiences. Secondly, only conference proceedings and journals are included to ensure timeliness of collected data.

Manual selection process. A manual selection process is applied during reading the abstracts to exclude literature with the following characteristics: (a) No architectural problems, challenges or requirements are described, (b) scope of the literature is too technical, and (c) literature is not accessible from the Reutlingen University network. As the identified literature is a sample, the abovementioned steps are performed to keep this sample as representative as possible to ensure valid results.

In line with Kitchenham [Ki04], more literature is identified through going backward by reviewing the citations for the articles identified in the aforementioned steps to determine prior articles that should be considered.

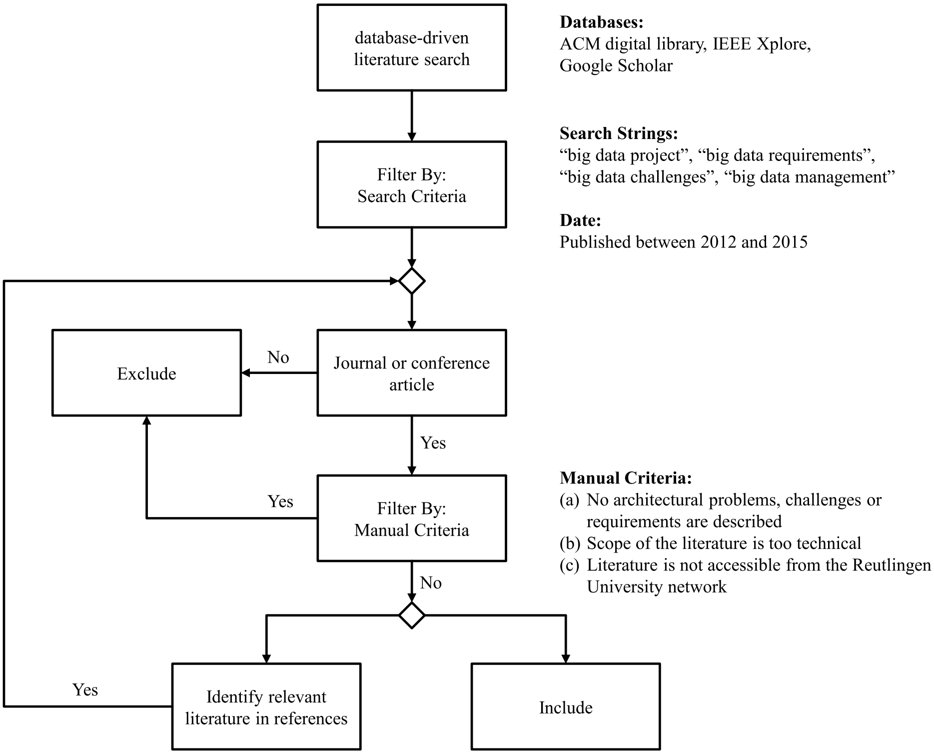

Fig. 1: Flow diagram of database-driven literature identification

The literature identification was conducted in the time between 05.11.2015 and 09.11.2015. Tab. 1 depicts the results of the described literature identification process.

Search string / Literature source	**Google Scholar**	**ACM digital library**	**IEEE Xplore**
"big data project"	23 results	1 result	1 result
"big data requirements"	1 result	1 result	1 result
"big data challenges"	4 results	1 result	2 results
"big data management"	9 results	1 result	4 results

Tab. 1: Results of database-driven literature identification

For the search in Google Scholar with the search strings “big data challenges” and “big data management” only the first 400 results were checked manually to consider economic aspects of the identification process. This leads to known problems such as the Matthew effect [BG09] and the Google Scholar effect [SD15]. The results of the described literature identification process provide the input for the analysis and interpretation to answer the underlying research questions.

4 Analysis and Interpretation

In this section, we answer the research questions presented in Section 1 by considering the outcome of the literature identification process. RQ1 and RQ2 deal with the requirements for EA management or challenges referring to EA management, respectively. RQ3 poses the question if approaches or methods do exist that consider EA management techniques. We therefore categorized the analyzed literature into three categories, namely requirement, challenge, and approach. Based on this categorization the research questions are answered.

RQ1: Which EA requirements do exist in the big data context?

Some papers mention EA requirements in the context of big data management and project implementation. But in general only few papers deal with requirements related to the EA management discipline, even if the design of system architectures is considered as key success factor [Ji15]. Buhl et al. delineate the alignment of IT infrastructure, business processes, applications and the business model as necessarily for long-term success [Bu13]. Whereas top management support is seen as relevant requirement to embed big data systems into existing structures [HE15], [RA15], [Ve13] only few publications describe the need for strategic initiatives to cope with the complexity of big data technologies, their integration and usage [KGS14], [RA15]. Nevertheless, mentioned requirements provide strong evidence for the need of a systematic EA management support in big data management [Ab14], [Ka15], [SC15], [Vo14]. Corbett et al. describe the need to frame big data to gain advantages of innovation within tradition and to balance technical and social integration efforts [CW15]. The current EA and big data projects have a bilateral relationship. While the current EA constrains the possibilities of these projects, it is also transformed by big data projects [HE15], [SC15]. Furthermore, big data projects require a flexible EA that allows easy data merging and tracking of documented data flows [Gr14], [Wi13]. Utilizing big data is only possible with a flexible IT architecture that backs the necessary core data infrastructure [Wi13]. Some authors describe the need for new methods dealing with data uncertainty and inconsistencies on a technical level as well as information in form of metadata to support high-level analysis and the assessment of opportunities for new solutions [KLD13], [Sa14]. Metadata provide a conceptual framework and the basis for analysis [Be13b], [KLD13], [SC15], [Ve13]. Metadata enable support in projects and strategic alignment of EA transformation processes. Semantic support, i.e. the understanding of data, is key to meet data needs [Ab14]. An EA model could be used as knowledge base that describes domain knowledge in form of the most important entities and relationships. A systematic strategy-oriented approach could provide architectural guidance and governance [Bu13].

Another important aspect is the collaboration of business and IT [AC13], [RA15], [SC15]. Complex data processing techniques may require the understanding and analysis of underlying assumptions at each stage of data processing [Be13b]. Cross-functional teams have to work closely [Ka15], complex skill sets are required [HE15], [SC15], and naming conventions have to be established to ease human perception and real-world entity representation [Fa12], [Ka15]. Conceptualization is a main constituent of EA modeling and corresponding EA modeling languages, respectively and can be used to support entity resolution [Sc11]. Since big data solutions have to be adapted to user requirements, Kanchi et al. recommend data modelling to meet enterprise data needs of customers [Ka15]. A focus on the user requirements helps to prevent the development of unnecessary technology solutions [KLD13]. Visualizations are a common instrument in EA analysis to support stakeholders of a linguistic community [KL96] in their individual tasks with relevant information [Ma08].

RQ2: Which challenges in big data projects referring to EA management do exist?

We found challenges in the context of big data management and project implementation that do not directly refer to the EA management discipline, but implicitly relate to EA management. The use of big data technology made existing data management techniques not directly applicable to the needs of the applications [Sa14]. Data differs from traditional use cases, are not transactional, and contain high degrees of uncertainty [Sa14]. Data are not seen as managed assets [Bu13] and pricing and data use management are not receiving enough attention [Ba15], [Ka13]. Kim et al. claim that big data is not used in an efficient manner and only utilized for rudimentary and surface-level analysis [KLD13]. Context for analyses is not provided [KLD13] and roles in the data life cycle are not managed adequately [Ab14]. Many authors describe the automated generation of meta data, which describe what data is recorded and how it is measured, as main challenge [AI13], [Ka13], [KLD13]. Relating generated data records to real-world entities [Ch13] and the usage in integrated analysis processes are a key success factor [AC13]. Therefore, people have to understand data meaning and use it to aid decision making [EE14]. Connecting a manifold stakeholder team and efficient collaboration is necessary to handle these challenges, but foster a change in system development processes and business activities [Ka13]. Only little research is done on this organizational impact of big data technology [SM13]. Organizational sensemaking processes can only be established if IT infrastructure opportunities are aligned with existing and future business processes and applications [Bu13], [CW15], [HE15], [SC15]. Among data management challenges such as data privacy [Kh14], data security [To13], intellectual property, liability [AC13], data quality and governance [Ka15], and data traceability, big data initiatives create a complexity that has not existed before. Data pipelines through many applications and business units are established and pose new challenges [SM13]. Therefore, organizations need appropriately skilled people such as data scientists [KTC14], [Wi13], enterprise level sponsorship [Ve13], and clear business cases to add value [Pa13]. Presented challenges in big data management and projects are often related to missing strategic initiatives which guide and prescribe the use of innovative technology aligned with the business strategy and business processes. Collaboration, alignment and data management can be supported by adapted EA management techniques to enhance big data usage and integration.

RQ3: Are there approaches or methods in big data management considering EA management?

Only few approaches considering EA management techniques have been identified. Approaches and methods in the papers provided by the literature identification process do not mention EA management explicitly, but make use of the same underlying principles. Abadi et al. recommend a building block approach to reuse existing system principles and provide best practice guidance on when to use each tool [Ab14]. These building blocks are only described for data analysis, but can be seen as instantiations of the concept of building blocks presented in The Open Group Architecture Framework (TOGAF) [Th10]. Kim et al. describe the use of metadata as means to manage big data [KLD13]. Meta data describe data and provide context for data processing and analysis processes. Abadi et al. recommend knowledge bases to capture domain knowledge about entities and relationships in a specific domain [Ab14]. EA management utilizes meta models to model the EA and visualizations to support stakeholders with relevant information [Ma08]. Conceptual modelling techniques and corresponding outcomes may be used in the domain of big data management to foster transparency and assess opportunities. We identified approaches using similar techniques as applied within EA management. Nevertheless, we could not identify approaches or methods linked to existing EA management to tackle big data challenges.

Included literature does not directly relate to existing EA solutions and is mainly focused on solutions for technical problems. Notwithstanding, we identified a couple of requirements mentioned in the identified conference proceedings and journals that can be related to EA management. Ideas for a potential usage of EA management solutions in the context of big data have been presented in this context. Furthermore, challenges have been analyzed and indicate a fertile application of EA management techniques to enhance big data usage and integration. A recognized common concept is information provisioning to foster the integration of new solutions in an existing EA, to support collaboration of stakeholders, to provide context for understanding and decisions making, and to align data management with the strategy. No systematic approach or method to relate big data management and EA management has been found. However, the SLR provides evidence that EA requirements play an important role in the big data context.

5 Conclusion and Future Work

This paper presents a systematic literature review to analyze which requirements and challenges mentioned in big data literature are related to the EA management discipline. Based on a described literature identification process in line with Kitchenham [Ki04], the underlying research questions have been answered by interpreting the identified literature sources towards a support by the EA management discipline. We used a systematic approach to foster research rigor. Nevertheless, the confinement to selected sources, the construction of search strings, and the necessary manual selection process represent limitations for robust and transferable results. The fact that this review only considers conference proceedings and journals to ensure timeliness trades completeness for relevance. In addition problems such as the Matthew effect [BG09] and the Google Scholar effect [SD15] have already been mentioned. Identified literature has to be interpreted towards the underlying research questions, since only few papers in this domain relate to EA management directly. The results embody a broad overview and a starting point for more detailed explorations. Evidence is provided that architectural requirements are a key success factors in the big data context and make an integration of big data management and EA management discipline necessary. Therefore, the presented research outcome is a first step towards the analysis of the alignment of the two disciplines.

Future research has to account for further steps. At first, we deem a systematic categorization of implicit and explicit junctures to EA management as useful means to frame incorporated requirements. Additionally, further steps should identify existing EA management solutions that can be applied to the defined problem space big data management. Current gaps have to be identified to foster future research and to further the evolution of the EA management discipline. The identified list of gaps may be extended and validated in case studies to assess their practical relevance.

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