Visual Analytics in Enterprise Architecture Management: A Systematic Literature Review

Dierk Jugel[1,2](✉), Kurt Sandkuhl[1], and Alfred Zimmermann[2]

[1] Rostock University, Rostock, Germany
{dierk.jugel,kurt.sandkuhl}@uni-rostock.de
[2] Reutlingen University, Reutlingen, Germany
alfred.zimmermann@reutlingen-university.de

Abstract. In times of dynamic markets, enterprises have to be agile to be able to quickly react to market influences. Due to the increasing digitization of products, the enterprise IT often is affected when business models change. Enterprise Architecture Management (EAM) targets a holistic view of the enterprise' IT and their relations to the business. However, Enterprise Architectures (EA) are complex structures consisting of many layers, artifacts and relationships between them. Thus, analyzing EA is a very complex task for stakeholders. Visualizations are common vehicles to support analysis. However, in practice visualization capabilities lack flexibility and interactivity. A solution to improve the support of stakeholders in analyzing EAs might be the application of visual analytics. Starting from a systematic literature review, this article investigates the features of visual analytics relevant for the context of EAM.

Keywords: EAM · Literature review · Visual analysis · Decision support

1 Introduction

In times of dynamic markets, enterprises in many industrial and service sectors have to be able to quickly adapt to changing market conditions or customer demands. In particular changes in the business models have several impacts on the enterprise architecture (EA) [1] including business processes, business units, information systems, and IT infrastructure. These architectural elements have manifold relations to each other which makes the EA a highly complex structure. Enterprise Architecture Management (EAM) is a method to support stakeholders in adaptation and transformation processes. Based on an up-to-date description of the enterprise model [2] and current EA, analyses are performed to understand adaptation needs and implications.

In practice, stakeholders commonly use visualization techniques and tools to analyze the EA. These visualizations, i.e. purpose-oriented or stakeholder-centered views on the EA, are usually created using EAM tools. However, as described in [3, 4], these tool-created views often are report-like, i.e. static with respect to the displayed information. As static visualizations do not sufficiently support interaction mechanisms for a detailed analysis of an EA, it is very time-consuming for stakeholders to work out relevant characteristics. From the perspective of business and IT-alignment [5], enterprise architecture can serve as planning and road-mapping support for the

W. Abramowicz et al. (Eds.): BIS 2016 Workshops, LNBIP 263, pp. 99–110, 2017.
DOI: 10.1007/978-3-319-52464-1_10

implementation of business requirements in appropriate IT-solutions. Improvement of visualization and analysis functions for EA models is expected to help stakeholder groups from both, business and IT, to identify relevant change needs in the EA and to improve understanding between each other.

In earlier work, we investigated this improvement potential of analysis and visualization features in EAM by using different techniques, such as cockpits [6], embedded real-time information in EA models [7] or decision modeling [8]. One research direction resulting from this work was to investigate the use of approaches from the field of visual computing. Besides different visualization techniques developed in this field, our attention was specifically attracted by the field of visual analytics (VA). According to [9] "Visual Analytics is the science of analytical reasoning facilitated by interactive visual interfaces". Visual analytics techniques for example can be applied to synthesize information and "derive insights from massive, dynamic, ambiguous, and often conflicting data". The authors of [7] define the following focus areas of Visual Analytics: Analytical reasoning techniques, visual representations and interaction techniques, data representations and "techniques to support production, presentation, and dissemination of the results of an analysis to communicate information in the appropriate context to a variety of audiences". Keim et al. [10] describe that in VA, algorithmic analyses performed by a tool are semi-automatically and interactively applied to the subject of analysis under consideration.

The aim of this paper is twofold: (1) to investigate which work already has been performed on using VA in EAM, and (2) to identify the most relevant lines of VA work for EAM.

With respect to the first aim, concepts of visual analytics seem not to have been applied in research: a recent survey on the state-of-the-art of visual EAM conducted by Roth et al. [4] does not identify any related concept in today's EAM tools. In order to widen and deepen this state-of-the-art work, we perform a systematic literature review (SLR) which has the main purpose to identify existing approaches targeting visual analytics in the context of EAM. For the second aim, we take the perspective of the well-accepted "scalability challenges" in visual analytics and discuss to what extent they are relevant and have to be addressed in EAM. The scalability challenges are considered as defining the roadmap for future VA research which makes them an interesting aspect for our investigation. The main contributions of this paper are a systematic account of visual analytics work in EAM and the discussion of relevance of scalability challenges in EAM.

Section 2 presents the approach of the systematic literature review including the process of paper identification, data collection and analysis. Section 3 addresses the relevant areas of VA for EAM by discussing the scalability challenges. In Sect. 4 we summarize the results.

2 Systematic Literature Review

This section addresses the question, which work on visual analytics in EAM has already be performed in scientific research. The section describes the research approach used, the data collection and the findings.

2.1 Research Approach

As a means to systematically identify the existing research about visual analytics in the field of EAM, we performed a SLR according to the guidelines of Kitchenham [11]. According to these guidelines, the SLR is a structured and comprehensive review process with the aim to "identify gaps in current research", provide "background in order to appropriately position new research activities" and collect all "existing evidence concerning a treatment or technology" [11]. Kitchenham [11] suggests six steps, which we document in the following and which guide the inner structure of the section.

Firstly, according to [11], we develop research questions (RQ) to be answered by the SLR:

RQ1: How much activity has there been in the field of Visual Analytics in EAM?
RQ2: What research topics are being investigated?
RQ3: Who is active in the research area?
RQ4: What approaches concerning Visual Analytics in the field of EAM are there?
RQ5: How are the VA scalability challenges in the context of EAM discussed in literature?

The research questions one to three deal with general issues to provide an overview about who addresses the research topic of applying visual analytics to EAM and in which context the topic is discussed. Research questions four and five focus on the application of visual analytics to EAM in detail. Whereas the goal of RQ4 is to identify literature that describes an application of visual analytics to EAM, the goal of RQ5 is to examine how the scalability challenges introduced in Sect. 3 are discussed in the context of EAM. Such discussions might be an indicator whether there is a demand for applying certain aspects of visual analytics to EAM or not.

2.2 Identification of Papers

In this section, we describe the process of paper identification. Firstly, literature sources have to be determined, which defines the overall search space. Subsequently, we describe the search process itself. For a better overview, at the end we give a summary about the search process for a better understanding.

2.2.1 Literature Sources

Before the search process can be performed, the literature sources to be taken into account have to be defined. We decided to examine the following five repositories that include important journals and conferences in the context of computer science and business information systems:

ACM digital library[1], AIS electronic library (AISeL)[2], IEEE Xplore[3], ScienceDirect[4], and SpringerLink[5]. This decision is based on the assumption that all work on visual analytics in EAM should reach one of these major outlets.

The Association for Computer Machinery (ACM) hosts conferences that are relevant to our research topic, like the conference on "Computer Supported Cooperative Work" (CSCW). The Association for Information Systems (AIS) hosts important and high ranked international conferences in the area of business informatics like "International Conference on Information Systems" (ICIS). AIS also is publisher of numerous high ranked journals like "Management in Information Systems Quarterly" (MISQ).

SpringerLink includes all papers and books published by Springer. This repository also includes important international conferences and journals in the area of business informatics like "Conference on Advanced Information Systems Engineering" (CAiSE) and the working conference on "Practice of Enterprise Modeling" (PoEM). IEEE Xplore Digital Library includes high ranked international conferences and journals like "Enterprise Distributed Object Conference" (EDOC), which are important sources in EA research. ScienceDirect is a repository that includes more than 200 journals in the field of computer science like "Information Systems".

2.2.2 Search Process

In this section we describe further steps of Kitchenham's review process. The next step to do is so-called "population" [11]. In this step the search string is developed. Afterwards the step "paper selection" is done by a manual selection of papers found by applying the search string on the literature sources defined in Sect. 2.2.1.

The Population. The aim of the SLR is to get an overview about Visual Analytics approaches in the field of EAM. To answer RQ5 we also added the scalability challenges to get an overview about papers that discuss these challenges in the field of EAM. The initial search string we developed is the following:

*("visual analytics" **OR** "information scalability" **OR** "software scalability" **OR** "visual scalability" **OR** "display scalability" **OR** "human scalability" **OR** "scalability challenge")*
AND
("enterprise architecture")

We applied this search string to the full text papers and all fields of the literature sources. Due to the fact that the research topic is relatively new and we do not expect many papers, we want to get all papers published in journals, conference proceedings and books from the past by the year 2015. We do not limit the publishing date, because sometimes it takes a while until proceedings of conferences are published in a repository. It may happen that proceedings of a conference hosted in 2015 are

---

1 http://dl.acm.org.

2 http://aisel.aisnet.org.

3 http://ieeexplore.ieee.org/Xplore/home.jsp.

4 http://www.sciencedirect.com.

5 http://link.springer.com.

published in 2016. In case we find papers of journals or conferences of 2016 we manually sort them out.

After performing the search, we only found 31 papers. Therefore, we refined the search string by adding synonyms for both “visual analytics” and “enterprise architecture” to increase the number of publications to get a better overview about current research. As a synonym for visual analytics we choose “visual analysis”. Heer and Shneiderman define visual analysis as an “iterative process of view creation, exploration, and refinement” [12]. In other words, visual analysis targets analyzing something by using (interactive) visualizations. Using this definition, visual analytics can be interpreted as a concretization of visual analysis. Visual Analytics and Visual Analysis paradigms are not the same. However, probably there are papers describing visual analytics mechanisms, but name it visual analysis. As a synonym for “enterprise architecture” we choose “enterprise model” because enterprise models also contain the elements (e.g. business processes and applications) that are part of an enterprise architecture. The refined search string we used for performing the SLR looks like the following:

(“visual analytics” ***OR*** *“visual analysis”* ***OR*** *“information scalability”* ***OR*** *“software scalability”* ***OR*** *“visual scalability”* ***OR*** *“display scalability”* ***OR*** *“human scalability”* ***OR*** *“scalability challenge”)*

AND

(“enterprise architecture” ***OR*** *“enterprise model”)*

We performed this search at June, 9th 2016 and found 70 papers (ACM: 0, AISeL: 6, IEEE Xplore: 20, ScienceDirect: 9, SpringerLink: 35). We also applied the refined search string to the full text papers and all fields of the literature sources without limiting the publishing date. With this search result at hand, relevant papers that are suitable to answer the research questions have to be filtered by reading the papers’ abstracts.

2.2.3 Paper Selection

In this step all abstracts of the 70 papers have to be read to select relevant papers for answering the research questions. For selecting relevant papers, we defined criteria. For us a paper is relevant if the authors describe an approach or a method to enable visually analyzing an enterprise architecture or an enterprise model. Thereby, the authors have to describe mechanisms like combining automated analyses and visualizations that outrun visual analysis approaches towards visual analytics. Moreover, the central part of the paper has to contain such an approach. Papers, in which the authors only mention that visual analysis or visual analytics may help for specific issues are not relevant for us. In addition, papers are relevant if the authors discuss scalability challenges in the field of analyzing enterprise architectures or enterprise models.

Before we read the abstracts, we excluded all found items, which are no papers. We filtered out 10 items, because they are table of contents, abstracts of books and so on. Afterwards we read the abstracts of 60 remained papers and identified only 7 relevant ones according to our criteria. In case of unclear situations, we read the full text to decide whether a paper is relevant or not.

2.2.4 Summary of the Search Process

We started with the population. In first step we applied an initial search string on the previously defined literature sources – the repositories ACM digital library, AISeL, IEEE Xplore, ScienceDirect and SpringerLink. However, only 31 papers are found. Therefore, we refined the search string by adding synonyms to cover a broader field of research papers. By applying the refined search string, we found 70 papers. These papers are the starting point for the identification of relevant papers. We defined criteria to determine which papers are relevant to answer our research questions. Before we started to identify relevant papers, we excluded all found items, which are no papers, because e.g. they are table of contents or abstracts of books. 60 papers were left over. After reading the abstracts we identified only 7 relevant papers, which we analyze in detail in Sect. 4.

2.3 Analysis of Data and Interpretation

In this section, we answer the research questions of Sect. 2.1 by using collected data of relevant papers identified in Sect. 2.2.3. RQ1 to RQ3 deal with general information about research topics, used research approaches, who is active and how much activity in the investigated field of research there is. RQ4 concerns the presented approaches of the papers itself. To answer this question, we give a short summary of each approach to get an overview about the current situation in research. RQ5 targets the papers that discuss scalability challenges in EAM.

RQ1: How much activity is in the field of Visual Analytics in EAM?

We found only 7 papers, which deal with visual analytics in EAM. Before we started this SLR we did not expect many papers, because experience from own practice shows that tools in EAM to a large extent offer only conventional reporting features and no visual analytics possibilities. Tool surveys and case studies like [3, 4] confirm this assumption, which do not cover visual analytics capabilities. The authors of [13] performed a research study investigating visual analytics capabilities of the EAM tools. As a result, in some cases first approaches concerning modern and interactive techniques for visual analysis exist. However, the visual capabilities of EAM tools mostly are limited on static visualizations without interaction possibilities. All these information indicates that visual analytics is a very innovative field of research in the domain of EAM.

Figure 1 illustrates the respective number of relevant papers by literature repository and year of publication. Only AISeL, IEEE Xplore and SpringerLink contain relevant papers. When we go in detail we see that 4 papers are workshop papers and 3 conference papers. The oldest paper we found was published in 2012. This situation also indicates that this field of research is relatively new and there is much research in progress. The Enterprise Distributed Object Conference (EDOC) is the conference with the most paper (3 workshop papers). There are no relevant papers in ACM digital library and ScienceDirect. ACM digital library only contains premium conferences. Therefore, this situation is not surprising, because the most papers are work in progress, which cannot be published in journals and it is very difficult to publish them in high ranked conferences. The situation of ScienceDirect is quite similar. This repository only contains journals.

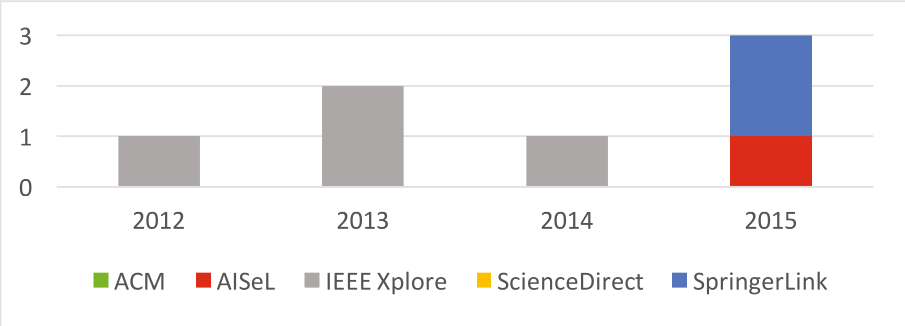

Fig. 1. Research activity by year

RQ2: What research topics are being investigated?

While reading the relevant papers, it appears that most of all address analyzing enterprise architectures [14–18]. However, the way how an EA is analyzed differs. Roth et al. address the topic of a business user-friendly configuration of visualizations [18]. An approach to analyze enterprise application landscapes and related monitoring data is presented by Fittkau et al. [14]. Visual analysis of EAs is focused in [15–17]. Naseer et al. present a tool to build up a data-centric EA by using semantic techniques to integrate different data sources and to make them accessible and analyzable [19]. The integration of different enterprise models by using visual techniques is also the focus of [20].

RQ3: Who is active in the research area?

The 7 papers are written by 13 authors. 4 papers are written by the same co-authors named David Naranjo, Mario Sánchez and Jorge Villalobos [15–17, 20]. All the papers describe the same approach in different stages of progress and focusing. Two papers are written by authors of the Technical University of Munich in Germany [14, 18]. Another one is written by Fujitsu Laboratories Europe [19]. Only one paper is written by a cooperation between Technical University of Munich and Kiel University [14]. All other papers are written by one institution. Summarizing it seems to be that research groups of the Universidad de Los Andes and Technical University of Munich are the only ones, which research in this field for years.

This situation is surprising, because the impact of this topic on practice is very high. An explanation for that could be that this topic is very practice-oriented, which maybe is more suitable for applied research than for fundamental research projects.

RQ4: What approaches concerning Visual Analytics in the field of EAM are there?

We identified 6 papers discussing visual analytics in the field of EAM. There are 3 papers, which describe the same approach in different stages of progress. In [16] the authors present an idea of visual EA analysis. The aim is to develop a metamodel-independent platform that is flexible and configurable. Based on this platform the authors want to combine automated analysis functions, which are composable, with visualizing the analysis' results. The combination of automated analyses and visualizing their results is a first step towards visual analytics. The platform is grounded on the so-called PRIMROSe framework, a proprietary development of the authors focusing on overview visualizations. The PRIMROSe framework is based on a so-called "pipeline of pipelines" [16]. The production of a visualization is a process consisting of 5 steps, which are connected via user interactions. A step for example corresponds to an analysis function or the transformation of the visual styling of the graph nodes according to the analysis' result. Each step is called a pipeline. A pipeline has defined inputs and outputs. Within a step the input is transformed into an output. A so-called platform pipelines consists of the pipeline of each step.

Whereas in [16] the authors describe the overall concept and idea, in [17] they go into detail and describe the EA visual analysis process and the prototype. Their visual analysis process starts with importing the EA model, followed by automatable analysis functions. Afterwards the analysis' results have to be visualized for stakeholders. Now stakeholders create hypotheses based on the information they can see. To ensure hypothesis, stakeholders interact with the systems by e.g. triggering further analyses or to filter information. As a result, a new visualization will be created, which leads to new information for the stakeholder. Now the stakeholder can decide what is to do next. The stakeholder is also able to communicate analysis results. Another use case of visual EA analysis is described by Naranjo et al. in [20]. In this paper they use PRIMROSe to integrate different enterprise models in a visual way. They use visualizations to connect same elements of different models. The authors present a tool named Sigourney based on PRIMROSe to do this integration.

Roth et al. present in [18] an approach of a business user-friendly configuration of visualizations. For this purpose the authors introduce a meta-information model, that includes technical information demands of abstract viewpoints and the information offer of an EA model. The technical information demand of an abstract viewpoint depends on the type of the visualization. For instance, a matrix diagram requires a concept of an EA model for the cells, and related concepts for x- and y-axis. The information offer of an EA model includes concepts and their properties and relations. In addition, the authors develop a structural pattern matching algorithm to bind visualizations and bindings. For non-technical users the authors provide a configuration wizard.

Fittkau et al. present an approach to visually analyze enterprise application landscapes and related monitoring data, like CPU workload [14]. The authors emphasize the importance of combining data about enterprise application landscapes with related real-time monitoring data to increase data quality of application landscape documentations and to take better decisions about the landscape. They demonstrate how to link several data sources using a tool called "ExplorViz" that provides interactive 2d and 3d visualizations on different levels of abstraction in real-time.

Naseer et al. describe in [19] an advance to build-up a data-centric EA. In companies there are many structured and unstructured information. The authors consider their tool as a visual analytics tool, because the tool provides interactive functions and visualizations to visualize analysis results.

RQ5: How are the VA scalability challenges in the context of EAM discussed in literature?

There are two papers that indirectly discuss scalability challenges. Naranjo et al. develop an evaluation framework to assess EA visual analysis capabilities of EAM and general visualization tools. For the framework, the authors identify 14 requirements important for visually analyzing enterprise models. The requirements “Keep the context (KC)” and “Focus of Interest (FI)” for us are especially of interest. Naranjo et al. argue that enterprise models can be very large and stakeholders often have problems to find one’s way. Therefore, they propose mechanisms “for encoding large models without losing the big picture” (requirement KC) [15]. In addition, stakeholders have to be able to dynamically choose the focus of interest. That implies that elements, which are especially of interest have to be highlighted whereas less important elements also have to be present, but in another way (requirement FI). The authors do not explicitly mention visual analytics’ scalability challenges, but the requirements KC and FI reveal problems concerning the adaption of data to the audience (information scalability) and effectively display massive data sets (visual scalability).

Roth et al. [18] point out dynamic information demands of stakeholders in EAM. However, the configuration of visualizations mostly is not trivial and often only can be done by experts. This leads to long-time configuration processes, which hinders ad-hoc analysis of stakeholders. The issue addressed by Roth et al. also targets information scalability.

3 Visual Analytics in EAM

The SLR discussed in Sect. 2 confirmed that nearly no work was done on visual analytics in EAM. Thus, we addressed our second aim to identify relevant areas from VA for the field of EAM. As guiding structure for discussing what parts of VA could be relevant for EAM, we selected the scalability challenges of VA. The five scalability challenges, which visual analytics should address, are information scalability, visual scalability, display scalability, human scalability, and software scalability (see below). In VA the five scalability challenges are considered as cornerstones in the roadmap of future VA research, which from our perspective motivates its use for investigating the relevance for EAM.

One of the motivations for performing the systematic literature analysis was to identify existing work and potentials of visual analytics in EAM. Since not much work was identified in the intersection of both subject areas “visual analytics” and “EAM” (see Sect. 2), this combination either is not relevant for EAM or there is room for additional research. Due to our impression that EAM tools still can be improved (see Sect. 1) our conjecture is that there is unexplored potential. Thus, we decided to analyze relevance of visual analytics in more detail and to base this analysis on the scalability challenges identified in this field. Scalability challenges initially were meant to identify future research directions for visual analytics but also can be seen as representing dimensions of functions in this discipline.

Visual analytics is expected to be in particular useful when large amounts of data have to be managed, analyzed and visualized. Especially large enterprises with an EA containing thousands of elements have the problem to handle large amounts of data. Five scalability challenges were identified, which visual analytics should be address: information scalability, visual scalability, display scalability, human scalability, and software scalability [9].

Information scalability describes “the capability to extract data from massive data streams”, to cope with quick change rates of information and to adapt information to the audience [9]. This scalability challenge clearly exists in EAM. As soon as EAM is linked to operational data reflecting the current status of EA elements, like application instances, process instances or technical systems, extracts from real-time data are required which have to meet the needs of decision makers. This also indicates the need to scale the information to the audience – in EAM many stakeholders in different roles are involved (see [21]). Therefore, it is important to provide information, which the stakeholder is able to interpret.

Visual scalability includes interaction techniques with visual representations and ability to effectively display massive data set, i.e. either a large amount of data elements or dimensions [9], for example by using appropriate visual metaphors. This can also be important for EAM cases if several thousands of application or systems instances are active in an enterprise, but does not have the same priority as information scalability.

Display scalability addresses the issue of different display resolution, sizes and other form factors [9] which, for example, require display scale-independent interaction techniques. In most enterprises, there are many different display types in use starting from conventional desktop computers to tables, smartphones and large screens in meeting rooms. Although EAM traditionally is done in desk work and meeting rooms, there are more and more tasks assigned to mobile users. Visual analytics functions available on different display forms probably would be well-received by EAM stakeholders.

Human scalability addresses the fact that analysis activities are not always done by single persons but by groups of people in different numbers. In such a collaborative setting, the different participants still need to have different tasks and problems they need to focus on. Such situations are quite typical for EAM scenarios as many roles are involved in analysis and decision making processes regarding enterprise architectures, i.e. human scalability seems to be very relevant to EAM.

The software scalability, which is described as the capability to “interactively manipulate large data sets” and addresses algorithms and approaches for scalable software [9]. In principle, scalable software systems for the management of enterprise architecture data are also important for EAM. However, in our opinion that aspect is not of highest priority since existing EAM tools seems to scale in an acceptable way.

Williams et al. investigate in [22] impacts on decision making by doing visual analytics. Traditionally reports or visualizations are created by experts that provides it to users like managers, enterprise architects and so on. Thus, visual analytics provides interactive functions to analyze data in an ad hoc manner, studying, analysis and decision making become an iterative process. The authors write about self-service analysis for decision makers and managers and “visual decision making” [22]. However, this has organizational impacts. The target group of visual analytics are decision makers and managers. Nevertheless, these stakeholders do not have expert knowledge about the information, because currently they get their packaged reports from experts. The stakeholders “only” have to interpret the data they see on the reports. Studying and analyzing the data require fundamental knowledge about the data, their structure and coherences.

Based on the above discussion, our conclusion is that all scalability challenges from visual analytics are to some extent relevant for EAM, i.e. visual analytics functionality of future EAM tools should observe these challenges and implement appropriate features. Thus, the challenges can be used as general requirements when designing future functionalities of EAM tools. Of highest importance are from our perspective information scalability and human scalability.

4 Summary and Future Work

Using a systematic literature analysis, we investigated the state of research on visual analytics in EAM. One of the analysis purposes was to explore, to what extent visual analytics techniques were applied in EAM research and what improvement potentials exist. The literature analysis showed that only a few papers and approaches address visual analytics in EAM, but these papers do not address the scalability challenges.

Furthermore, we discussed the scalability challenges from visual analytics and their relevance for EAM. From our perspective information scalability and human scalability are of highest importance for implementation in EAM tools.

We are planning to use the different scalability dimensions for analysis of established EAM tools in order to identify improvement potentials. As a precondition, the scalability challenges need to be operationalized in a catalogue of more concrete functionalities which indicate their support in the tool and which support the possibility of differentiation between tools. Furthermore, we plan to use the same operationalization for investigating EAM stakeholder opinion about the need for respective functions. Both views, i.e. the extent of existing features in tools and the requirements from user side, are expected to help in setting priorities for tool improvement.

References

1. Ahlemann, F., Stettiner, E., Messerschmidt, M., Legner, C.: Strategic Enterprise Architecture Management: Challenges, Best Practices, and Future Developments (Management for Professionals). Springer, Heidelberg (2012)
2. Sandkuhl, K., Stirna, J., Persson, A., Wißotzki, M.: Enterprise Modeling: Tackling Business Challenges with the 4EM Method. Springer, Heidelberg (2014)
3. Matthes, F., Buckl, S., Leitel, J., Schweda, C.M.: Enterprise architecture management tool survey 2008, München (2008)
4. Roth, S., Zec, M., Matthes, F.: Enterprise architecture visualization tool survey 2014, München (2014)
5. Seigerroth, U.: Enterprise modeling and enterprise architecture. Int. J. IT Bus. Alignment Gov. **2**, 16–34 (2011)
6. Jugel, D., Schweda, C.M.: Interactive functions of a cockpit for enterprise architecture planning. In: 2014 IEEE 18th International Enterprise Distributed Object Computing Conference Workshops and Demonstrations, pp. 33–40 (2014)
7. Christiner, F., Lantow, B., Sandkuhl, K., Wißotzki, M.: Multi-dimensional visualization in enterprise modeling. In: Business Information Systems, Vilnius, pp. 139–152 (2012)

8. Jugel, D., Kehrer, S., Schweda, C.M., Zimmermann, A.: A decision-making case for collaborative enterprise architecture engineering. In: Lecture Notes in Informatics (LNI) - Informatik 2015, pp. 865–879. Gesellschaft für Informatik (GI) (2015)
9. Thomas, J.J., Cook, K.A.: Illuminating the path: the research and development agenda for visual analytics (2005)
10. Keim, D., Andrienko, G., Fekete, J.-D., Görg, C., Kohlhammer, J., Melançon, G.: Visual analytics: definition, process, and challenges. In: Kerren, A., Stasko, John, T., Fekete, J.-D., North, C. (eds.) Information Visualization. LNCS, vol. 4950, pp. 154–175. Springer, Heidelberg (2008). doi:10.1007/978-3-540-70956-5_7
11. Kitchenham, B.: Procedures for performing systematic reviews, Keele, UK (2004)
12. Heer, J., Shneiderman, B.: Interactive dynamics for visual analysis. Queue **10**, 30 (2012)
13. Jugel, D., Schweda, C.M., Zimmermann, A., Läufer, S.: Tool capability in visual EAM analytics. Complex Syst. Inf. Model. Q. **2**, 46–55 (2015). doi:10.7250/csimq.2015-2.04
14. Fittkau, F., Roth, S., Hasselbring, W.: Explorviz : visual runtime behavior analysis of enterprise application. In: ECIS 2015 Completed Research Papers (2015)
15. Naranjo, D., Sanchez, M., Villalobos, J.: Visual analysis of enterprise models. In: 2012 IEEE 16th International Enterprise Distributed Object Computing Conference Workshops, pp. 19–28 (2012)
16. Naranjo, D., Sanchez, M., Villalobos, J.: Towards a unified and modular approach for visual analysis of enterprise models. In: 2014 IEEE 18th International Enterprise Distributed Object Computing Conference Workshops and Demonstrations, pp. 77–86. IEEE (2014)
17. Naranjo, D., Sánchez, M., Villalobos, J.: PRIMROSe: a graph-based approach for enterprise architecture analysis. In: Cordeiro, J., Hammoudi, S., Maciaszek, L., Camp, O., Filipe, J. (eds.) ICEIS 2014. LNBIP, vol. 227, pp. 434–452. Springer, Heidelberg (2015). doi:10.1007/978-3-319-22348-3_24
18. Roth, S., Hauder, M., Zec, M., Utz, A., Matthes, F.: Empowering business users to analyze enterprise architectures: structural model matching to configure visualizations. In: 2013 17th IEEE International Enterprise Distributed Object Computing Conference Workshops, pp. 352–360. IEEE (2013)
19. Naseer, A., Laera, L., Matsutsuka, T.: Enterprise BigGraph. In: Proceedings of the Annual Hawaii International Conference on System Sciences, pp. 1005–1014 (2013)
20. Naranjo, D., Sánchez, M., Villalobos, J.: The devil in the details: fine-grained enterprise model weaving. In: Persson, A., Stirna, J. (eds.) CAiSE 2015. LNBIP, vol. 215, pp. 233–244. Springer, Heidelberg (2015). doi:10.1007/978-3-319-19243-7_23
21. Wißotzki, M., Köpp, C., Stelzer, P.: Rollenkonzepte im enterprise architecture management. In: Zimmermann, A., Rossmann, A. (eds.) Digital Enterprise Computing (DEC 2015). Lecture Notes in Informatics (LNI), vol. P-244, pp. 127–138. Gesellschaft für Informatik, Böblingen (2015)
22. Williams, B.G., Boland, R.J., Lyytinen, K.: Shaping problems, not decisions: when decision makers leverage visual analytics. In: Twenty-First Americas Conference on Information Systems (AMCIS 2015), pp. 1–15. Association for Information Systems (AIS), Puerto Rico (2015)