A Self-Service Supporting Business Intelligence and Big Data Analytics Architecture

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Abstract. Self-service Business Intelligence (SSBI) is an emerging topic for many companies. Casual users should be enabled to independently build their own analyses and reports. This accelerates and simplifies the decision-making processes. Although recent studies began to discuss parts of a self-service environment, none of these present a comprehensive architecture. Following a design science research approach, this study proposes a new self-service oriented BI architecture in order to address this gap. Starting from an in-depth literature review, an initial model was developed and improved by qualitative data analysis from interviews with 18 BI and IT specialists form companies across different industries. The proposed architecture model demonstrates the interaction between introduced self-service elements with each other and with traditional BI components. For example, we look at the integration of collaboration rooms and a self-learning knowledge database that aims to be a source for a report recommender.

Keywords: Business Intelligence, Big Data, Architecture, Self-Service, Analytics

1 Introduction

Companies' market capitalization generally consists of enormous amounts of data available to them. However, several companies struggle to use these large amounts of data for analysis or for a decision support as data is often not easily accessible to business users [1]. Business Intelligence (BI) describes the process from collecting data to a fact-based decision support. This decision support is extending from strategic questions into operational environments [2]. This leads to the demand to enable more users to use BI systems. Many companies have to make these decisions in a time-critical environment, which increases the need for a faster technical infrastructure. It is crucial to consider the time a department needs to access the relevant information. Self-service BI (SSBI) provides a solution to these demands. SSBI aims to "empower casual users to perform custom analytics and to derive actionable information from large amounts of multifaceted data without having to involve BI specialists. Power users, on the other hand, can accomplish their tasks with SSBI more easily and quickly than before." [3]

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Not only the importance of self-service BI rises but also big data analytics is an emerging topic [4]. The increasing volumes of data and the need for advanced analytics means that BI architectures must be adjusted. Many papers discuss parts of a self-service environment but not a whole self-service BI/big data architecture (e.g. [5], [6], [7]). This leads to the following research question:

> *RQ: How is a self-service supporting BI/big data analytics architecture constructed?*

The proposed BI/big data analytics architecture model supports standardized BI reports and new big data analysis, and also enables power users to build their own reports. The research design is described in the next section. After that, the relevant literature is presented. Next, the new architecture and the self-service supporting elements of the collaboration rooms and the knowledge database are explained. Finally, recommendations and implications are given and discussed. Further, the limitations are named and further research is addressed. The paper ends with conclusions.

2 Research Design and Methods

In order to ensure methodological rigor, this study utilizes design science research as the underlying methodology as it is well suited for the development of an architecture. Mainly we were guided by the Design Science Research Model (DSRM) proposed by [8]. Figure 1 shows the phases and the steps that were carried out. Using a literature review based on Webster and Watson, relevant BI and big data architecture models were discussed and a research gap was identified [9]. In the next step ("Objectives definition") SSBI literature was analyzed and demands from practice were included. With these insights a conceptual model was developed. Open semi-structured interviews helped to improve the model in the "design & development" phase. This research method makes a free discussion about the problems and requirements of SSBI possible. Eighteen experts from different industries were interviewed (see table 1). Each expert had at least two years of experience with BI and on average, they had ten years. The interviews lasted on average one hour. The interviews were transcribed and analyzed by categorizing the main statements. Mayring's method makes qualitative statements comparable by analyzing the frequency in which they were mentioned [10]. The improvements were incorporated and the changed model was shown to the experts again. The new improvements were implemented in the next step.

Table 1. Interviewed experts

Job Group	*Expert Number*
Business consultant	1-3
SAP consultant	4-8
BI application developer	9-13
IT manager	14-18

The demonstration and evaluation phase of the original Peffers et al. model was summarized with an applicability check [11]. A focus group consisting of eleven researchers and a group consisting of twelve practitioners discussed the model with regard to whether it adds value for research and practice and whether it can specifically help in the implementation of SSBI.

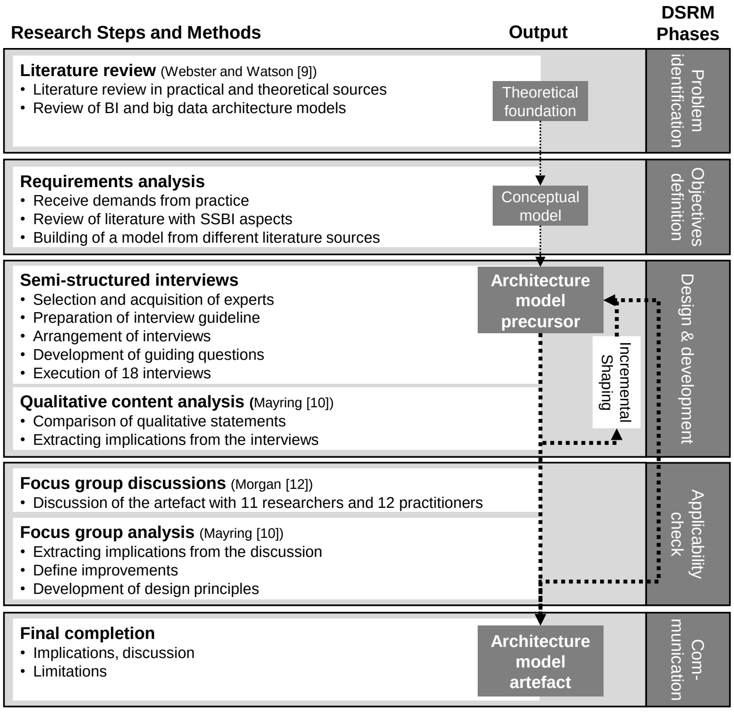

Figure 1. Research design based on [8]

3 Proposed Self-Service Supporting Architecture

3.1 Status Quo and Problem Identification

To identify the status quo of the SSBI research, a literature search was done in the AISeL, ScienceDirect, IEEEXplore, ACM and Emerald database. It was extended to include practitioner resources. Whitepapers by the BeyeNETWORK, The Data Warehousing Institute (TDWI), and Gartner were analyzed. The search keywords we used contained: “Self-Service” in combination with “BI”, “Business Intelligence”, “Big Data”, “Architecture” and “Analytics.” The publication dates ranged from 2005 to the present. The search resulted in 1,258 potentially relevant articles. They were reviewed by title and unsuitable papers were eliminated. If the title did not make a clear decision possible, the abstract, the introduction, and the conclusion were consulted. After that a forward and backward search in the most relevant papers was conducted. This included non-academic literature like whitepapers. Forty articles were deemed highly relevant for the development of the model. The literature review identified eight different BI or big data architecture models. Phillips-Wren et al. propose a big data analytics architecture model based on different other models [4]. The authors analyze existing BI/big data literature and describe a new user group they call data scientists. In the field of data processing infrastructures, Phillips-Wren et al. focus on the use of Hadoop clusters as a solution for big data use cases. Another model proposes a service-orientation character for a BI architecture [13]. They developed a BI architecture model that shows how this service character is implemented and which elements are necessary. Their model does not consider big data analytics use cases in particular. Another model is provided by [46]. In their work they focus on a mapping layer and a semantic layer which should be between the users and a data warehouse. A paper by Imhoff describes the different tracks for data processing in a big data environment [14]. It is a similar idea to the concept of a lambda architecture [15]. None of the previously discussed models make any statements about SSBI. The models by Watson and Eckerson provide some ideas for an implementation of SSBI [16-17]. Watson improved on Eckerson's model. The two models illustrate the difference between top-down and bottom-up BI. Top-down BI describes a BI environment that is very predefined and fixed whereas Bottom-up BI is an open environment that is not predefined [18]. Both models only differentiate between two user groups. [19] developed a model with a focus on SSBI. Their model describes different data processing methods, has a semantic layer, and covers big data analytics use cases. But they do not deal with different user groups. Another concept is to support SSBI with a business level ontology [20]. This is supposed to make the data model more comprehensible for the end user. [21] also propose a semantic layer to realize a unified business view of the data.

3.2 Requirements: Existing SSBI Aspects in Literature

In the second phase of the research design the objectives have to be defined. This is done by reviewing additional literature describing certain aspects of the implementation of SSBI. They can be separated into five groups: Special SSBI governance aspects and guidelines, concepts for an individual BI usage, social media elements in a BI environment, collaboration concepts and concepts for a knowledge database. This is summarized in table 2. Papers with special SSBI governance aspects and guidelines deal with changes in BI/big data analytics governance strategies [22], different ETL ("extract", "transform" and "load") processes [23], the need of special tools [24] or SSBI guidelines [25], [21], [26]. The individual BI usage group includes papers which describe concepts for an individual use of the BI environment. The idea of the integration of social media elements into a BI environment is to support the usage and the collaboration of BI users. Collaborative BI comprises the cooperation in the creation of reports or queries. In this context, it means human cooperation and not the grouping of systems. It is stressed that collaborative BI is not simply an element that has to be implemented into a BI architecture in terms of a technical platform; it also has to begin in the minds of employees [27]. The last group of papers considered deals with a knowledge database. The idea behind it is that the construction of every analysis and report is saved in an additional database. This includes the history of the conducted analyses and the order of their execution. Through that, forecasts of analysis paths should be possible.

Table 2. Overview SSBI literature

SSBI aspects	*Description*	*Sources*
Governance and guidelines	Changes in governance and guidelines for the realization of SSBI	[21-26]
Individual BI usage	Concepts which support an individual BI usage	[5-7], [28-30]
Social media elements	Social media elements in a BI environment	[31-32]
Collaboration	Cooperation in the creation of reports or queries	[5], [25], [27], [33-35]
Knowledge database	Database which saves construction and usage of reports and analyses; also examination of analysis paths	[36-41]

A combination of these elements with a comprehensive BI/big data analytics architecture is still missing. In the following, the focus will be on the architecture itself, the implementation of collaboration rooms, and a self-learning knowledge database. The collaboration rooms can then be connected with existing enterprise social media systems. After developing a first model with the findings from literature the model was improved through expert interviews. The following table 3 shows some of the major changes caused by the expert interviews.

Table 3. Improvements through expert interviews

Model layer	*Description*	*Sources*
Preparation	Multiple data access methods added; added direct access without using a storage system	Experts 1, 5, 7, 11, 13
Storage and analysis infrastructure	Generalization of the storage and analysis infrastructure into three tiers	Experts 1, 3, 6, 15-16
Presentation	Enterprise social networks added, skills added	Experts 4, 11
Knowledge database	Feedback loop added, development of the different use cases of the knowledge database	Experts 2, 4, 12, 15, 16
Governance	Order of the governance aspects according to by the experts mentioned importance	All experts had influence

3.3 Model Overview

In the following, the final model developed with the help of expert interviews is explained. Inspired by existing BI/big data analytics architecture models, the aim is to describe the whole process from the data sources through to the presentation of information. Big data is defined as “a phenomenon characterized by an ongoing increase in volume, variety, velocity, and veracity of data that requires advanced techniques and technologies to capture, store, distribute, manage, and analyze these data.” [42] This is the reason for the need of an advanced technical infrastructure. The changed technical infrastructure leads to a more complex data access for users which effects the possibilities of SSBI and the need to discuss the entire BI process from the source systems to the presentation of the data.

On the left side of the model are the data sources. The data sources are separated into internal and external sources. The data origin shown in Figure 2 are examples of those sources. The next step in data processing is the preparation of the data. Three different ways of accessing data exist. The first one is a direct access tunnel for analysis, where a special integration or caching of the data is not necessary. Second, direct access for real-time analysis is shown. The third method is a classic ETL process. But this process is extended by the possibility of performing an EL(T) process [43]. EL(T) stands for "extract", "load" and an optional "transform" process. This takes into account that in some big data analysis there can be a need for raw data that is not transformed. Different data access methods have to be taken into account for realizing SSBI. This is especially important for data scientists, who need access to raw data. In the proposed model, the storage and analysis infrastructure layer consists of two main and one optional tier. An element for data integration is necessary in every BI or big data environment. The job can be done with a classic data warehouse, but other technologies can take on this job, such as in-memory databases or Hadoop clusters. The other tier is the "big data refinery." This element ensures the necessary infrastructure for big data analysis and includes "experimental platforms." These platforms are essential for the data scientist user group. They need possibilities for experiments where data from different sources can be staged, merged, and analyzed [44]. The last tier consists of optional elements that could be necessary for a real-time BI realization, such as data caches [45]. To simplify access to data across multiple systems, there is the semantic layer which also includes the mapping layer described in [46]. It realizes a unified access to the different storage systems and an easier access to the data for users with low technical skills. A possible embodiment of the semantic layer could be a service oriented architecture. A service oriented BI architecture is described in the work by Pospiech and Felden [13].

The presentation of the data is separated into three portals. This separation is done according to the skill and the need of the BI user. In the dashboards, the users are consumers of predefined reports and they have a low degree of freedom [16-17]. Dashboards are mainly used by casual users. On the other side is the group of data scientists. In their data laboratory they have a high degree of freedom, as well as the access rights and tools to completely build their own analysis and reports. As mentioned above, they need platforms for experiments with new analyses because they are dealing with large and unstructured data sets. Between those two platforms the analytics portal is located. This is the main platform for SSBI applications. Reports are predefined but users can adjust the reports with restrictions. In general, the experts agreed with this representation. Some experts had a slight different user group definition in their own company like Watson also distinguishes between five user groups [44]. These user group definitions can therefore be adapted to the individual needs of the respective company. This is expressed in the following quote: *"Sure, there might be sub-groups, especially within the group of the power users and in the data scientists. But I think with three groups it is quite concise. Those are the right groups in the model. It is also* *meaningful to distinguish the groups by the user skill."* (Consultant, mid-sized consulting firm - interview conducted in German)

In addition to the definition of the different user groups, one expert added that the interaction between the portals plays an important role in supporting SSBI. *"The transition must be very fluent. The dashboard must be easy to use and allow a simple jump into details. So you need to have a drill down functionality. The continuity is important and just the same the usability. One must like to use the tool or the portal, because it is easy to use."* (Head of a quality management department, mid-sized industrial company - interview conducted in German)

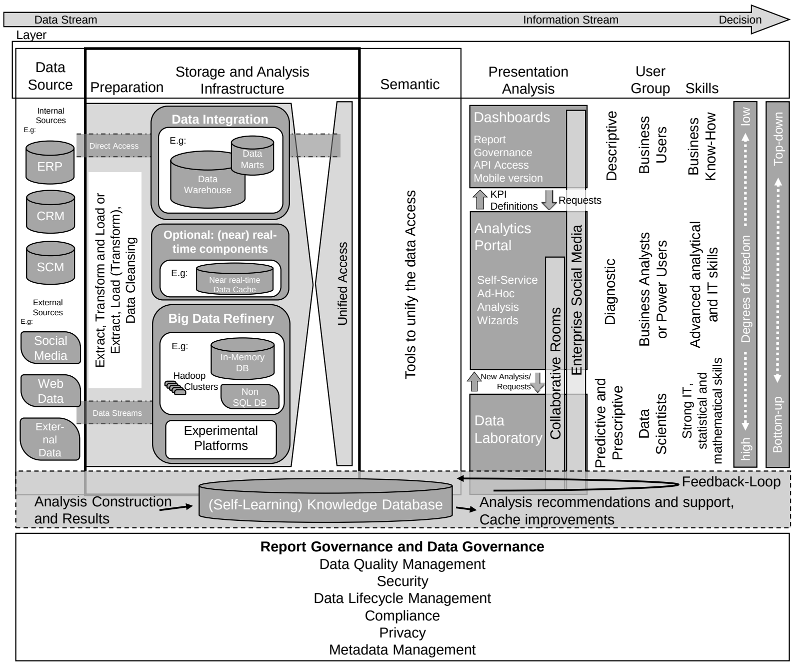

Figure 2. Proposed architecture model

To support the interaction the developed model is connected to an enterprise social network of the respective company. In that way the collaboration rooms can be merged with the enterprise social network and the exchange between the user groups can be encouraged. Below the model different aspects of a report and data governance are mentioned. They are ordered according to a ranking by the experts.

After giving a rough overview of the model the two main elements for the support of SSBI are described.

3.4 Collaboration Rooms

The "collaboration room" architectural component is a platform where a direct cooperation from users of the analytics portal and the data laboratory is possible. Users of the same portal can cooperate while working on the same platform. Also, users of the analytics platform can give feedback for analyses performed by data scientists. Business analysts can also ask for special sub-parts of their analysis to be built by data scientists. It is important for the process that the collaboration history is saved. Today most collaboration communication is done by email. The problem is that only the people involved have access to the origin story of a decision-making process. A collaboration platform can replace email communication. [25]

Figure 3 shows proposed classes of a collaboration room environment. It represents the different user groups and the related platforms. Business users and analysts can create requests for a new report or analysis. Business analysts can also ask for help with the construction of a report. The collaboration can take place inside a user group or business analysts can make requests to data scientists. These requests are connected to one or more reports. Every report belongs to a workspace. This is the main room where the collaboration can take place. Inside a workspace it is possible to create several communication rooms. One-on-one and group discussions are possible. The workspaces in conjunction with the communication rooms provide the opportunity for discussing reports, creating different report versions, and conducting experiments. All these elements support the collaboration between the different user groups of the BI/big data analytics architecture.

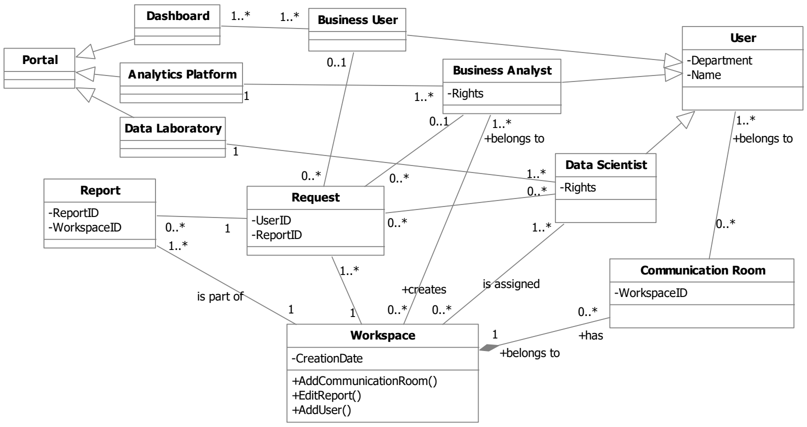

Figure 3. Collaboration environment conceptual class chart

3.5 Self-learning Knowledge Database

The knowledge database saves all performed queries except special experiments in the data laboratory. This includes the results of the queries as well as the queries themselves. It is useful to keep the queries for later use because they can have enormous value for later analyses. An historic analysis database creates the possibility for the replication of an analysis, which makes the building of new complex analysis easier. Here a service orientation shows its advantages because it is possible to easily see which components and services were used by different analyses. There is also added value generated by the possibility of showing related analyses [35]. This helps a business analyst build a new analysis or find further queries that were created in the past or by another user. [36], [39]

After conducting the expert interviews, several reasons for the introduction of a knowledge database were identified. The main reason is to improve SSBI with recommendations for similar analyses or by supporting the developing process of analyses [35], [38]. It can help to improve dashboards because with the database, it is known how often a report was accessed. Another important point is that the knowledge database helps to fill a cache in advance. This is made possible by the self-learning mechanism, which allows predictions. If we know which analyses are accessed frequently, the results can be computed in advance and saved into the cache. Then, fewer calculations have to be computed because the results are already in the cache, which decreases the response time. The prediction of queries can also be done by using Markov models [41].

Figure 4 shows a class chart of the proposed knowledge database. It represents the three potential use cases: Help while building new reports or queries, recommender for further analyses that might be interesting for the user, and intelligent filling of caches. A user builds or calls an analysis. This call is written into the knowledge or meta database just like the analysis path. The analysis path consists of the order and the connected queries a user calls in a session [40]. With the learning engine, all the data from the meta database is analyzed. Intelligent algorithms look for relations inside the queries and between the analysis paths. Different learning engines with different algorithms are possible.

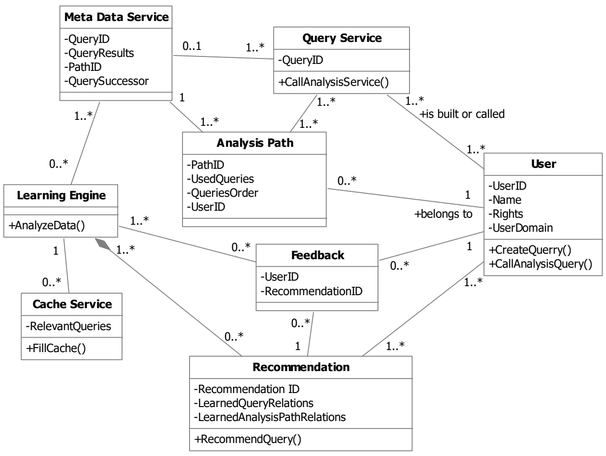

Figure 4. Knowledge database conceptual class chart

A problem could be that big amounts of data are necessary for meaningful results. This was already discussed with the experts: *"What you really need is: First you need a lot of different executions on top of your system. So it won't work in a single enterprise because you won't have enough data for your analytics of the analysis templates or mechanism that work and you need very good feedback functions. So you need to look in the usage data. So what is used and what is successful. […] I think that it will be very hard to build it on premise. It is something that works in pretty large companies because* *otherwise there is not enough usage for this."* (Vice President Platform, cloud BI provider) The results of the learning engine is then used by the recommender engine and the cache service. For the learning process it is essential to have a feedback loop. This means that the user can evaluate the results of recommendation. This feedback is then used by the learning engine for the improvement of the recommendation processes.

4 Implications, Recommendations and Discussion

The aim of academic literature is not only to focus on theory, but also to provide relevance for practitioners in order to prevent research from becoming an end unto itself [11]. For this reason, an applicability check was done after the final model was developed. In two focus groups consisting of practitioners and researchers, it was discussed whether the model can help realizing SSBI. In general, it was stated that the architecture model is helpful because it reduces complexity and gives companies a point of orientation. It was further remarked that for an application in practice, it must be defined further which use cases are relevant for SSBI. The focus groups also discussed potential main user groups in a SSBI environment. The discussion participants thought that it might be a user group that has ad-hoc questions that are not regular. They stated the need of a semantic layer and discussed that a service orientation as described in the model [13] is useful, but it requires a high degree of standardization in processes for the acquisition of information. This is a big problem in companies because these processes are mostly unknown. In the company of the focus group members the aim is to use '*Business Objects Universes'* for the realization of a semantic layer instead of realizing a complete service oriented architecture. In further projects '*SAP Business Objects Design Studio'* will be used for the creation of dashboards and '*Analysis for Office'*, an Add-In for *'Microsoft Excel'*, should be used for the analytics portal of the architecture. A data laboratory is not planned at the moment. The knowledge database can help new users in particular because they can get an idea of what information is available. This is supported by the statement of one expert: *"A typical use case for our big customers is that if you are a user and you create a new report then you have 99% chance that somebody else has already done this report. Exact this report! So that is the simplest thing. You can just search the report, look at the structure, look at the dimensions or whatever components the user is working with and start with what is already there. The second thing is some kind of recommendation. In our case it can be driven by what people will be doing."* (Vice President Platform, cloud BI provider)

Another point is the meaningfulness of the collaboration rooms. A different expert describes the value that is generated through a well-organized collaboration, but notes that there are still good implementations missing. *"I think this is valuable and useful because I think this should be the way into the future. Get out of the habit of each person making his or her own report, but that you can also reuse more of the reports. […] However, in reality it is not so simple to find platforms that make the realization possible. I have not yet seen and experienced properly implemented collaborative rooms in practice."* (Consultant for SAP BI, consulting firm - interview conducted in German) Table 4 summarizes the findings of this research in design principles. Besides these design principles the main output of this research is the architecture model which is presented in Figure 2. It shows the interaction between the elements and their position in the BI/big data analytics process.

Table 4. Design principles

Architecture element	*Design principle*
Data access	The data access via different data sources should be simplified by a unified access. This paper proposes a service orientation for the realization.
Semantic layer	To achieve a unified access to the data there should be a semantic layer which connects the different data sources. This could be in a service oriented but the applicability check showed that other realizations are possible, too.
User groups	To address the individual needs of the BI users, a definition of different user groups is necessary. This paper proposes three different groups but point out that this has to be adjusted according to the structures of the respective company.
Different portals	To address the different needs of the user groups, different portals are suggested.
Collaboration	Collaboration opportunities should be considered in a BI/big data analytics architecture. Enterprise social media can support the collaboration in a BI/big data environment.
Knowledge database	A knowledge database should be used in conjunction with a service oriented architecture to assist new users, for an intelligent cache usage and to help users with building new reports.

In the following section, the results of this research are described and compared with existing work. In terms of a semantic layer, as proposed in the literature [28], [30], the developed model stays universal but sees advantages in a service-oriented approach [13]. This is a concrete solution and it is assumed that this service orientation can be handled well in the knowledge database. Elements like a service repository are seen as being useful in supporting SSBI. Some experts criticized the fact that a service orientation would require a lot of effort in the beginning to standardize all the processes and services. The focus group decided that this might be a general problem of SSBI. The right balance must exist between standardization and flexibility.

In a big data analytics architecture, a new storage and analysis infrastructure is necessary. This paper connects the idea of many big data contributions [4], [17-16], [19] and assigns the new technologies to three tiers, similar to other proposals [14-15]. Especially the big data refinery in conjunction with experimental platforms are important for the independent work of the data scientists. The presented user groups are similar to the definitions of other research [4], [6]. The expert interviews showed that these definitions can be found in practice, but the probability of deviations in practice is high. Therefore, it is important to know the user groups of the BI architecture in order to correctly address the individual needs of each user group in an SSBI context. As mentioned by one of the experts, there is a need of fluent transitions between the portals.

The knowledge database can also support SSBI. It can contribute to an intelligent filling of analysis caches [41] and can recommend further analysis for users, which especially helps new and unexperienced users [36-39]. Analysis knowledge can be preserved with the use of the knowledge database. Nevertheless, the self-learning function is only realizable if enough data is available. This restricts the use of the self-learning function to large companies or to the use in a cloud environment. Research is moving towards presenting a class chart to give a better idea of how a self-learning knowledge database can be built. This enables storing implicit knowledge of BI users which facilitates an increased value for companies. This is supported by the results by Kretzer et al. [39] who find out that the ease of use of a BI platform is higher with a recommendation system. But they do not consider historical data and therefore they not have included learning loop. The developed collaboration rooms are based on the paper by Berthold et al. [25]. A more concrete implementation possibility is presented and the different user roles are shown. [33] describe another approach with the reformulation of queries in a peer-to-peer network. The collaboration rooms can be seen in connection with enterprise social media elements [31-32]. The expert interviews and the focus group discussion confirmed that the value of collaboration in a BI/big data analytics context will increase and collaboration rooms are a solution for that. It is suggested that collaboration rooms are included into companies' BI/big data analytics strategies as presented in Figure 3.

The whole architecture helps companies define their expectations of a BI/big data analytics architecture. When comparing an existing architecture with the proposed model, weak points and improvement potential can be shown.

5 Limitations and Future Work

A rigorous literature review was conducted. Nevertheless, this method has limits. The search was only done with keywords in English. Publications in other languages could not be considered unless they could be found by means of a forward or backward search. Eighteen interviewees were asked for critique and improvements. To obtain more objective opinions, a larger number of interviews would be useful. This could reduce the likelihood that important aspects are forgotten or misrepresented. The background of the experts is rather homogeneous. Most experts are BI consultants or BI developers who are good at discussing the overall architecture. The opinions of business users are still missing. Further research could use these opinions to improve the design of the presentation layer. Especially in relation to SSBI, their view might still be a significant enhancement. Furthermore, different business sectors were not considered. Thus, no statements about the adaption of the architecture to specific branches is possible. Further research can be done by asking how the architecture must be adjusted according to a special domain or how different sizes affect the architecture. It is obvious that the architecture has to be adjusted individually for every company. It was mentioned by the experts, for example, that the realization of a self-learning knowledge database is highly dependent on the amount of potential input data. If a company is not big enough to provide a sufficiently large amount of reports, inquiries, and analyses, there might not be enough input data. The recommendation function is then very limited because the learning algorithm does not get enough data. In such a case, only a simple knowledge database without self-learning algorithm could be realized. Statements about the amount of required data for a good working self-learning BI recommendation algorithm are not possible. Further research is needed with respect to that area. A self-learning knowledge database prototype should be developed. This could enable further discussions on this issue. The alternative would be a cloud-based knowledge database. By analyzing the reporting and analysis paths of several companies, a cloud implementation could deliver meaningful recommendations. But for that to happen, many architecture components would have to be moved to the cloud. Another question is which algorithms can be used to get useful results out of this analysis. The inclusion of the actual decision into the BI process is an outstanding research question. In this context, it could not be explored to what extent the actual decision can be included in the knowledge database.

6 Conclusions

The developed model shows significant progress in relation to other proposals [4], [16]. It is extended especially with regard to SSBI. The ideas result from both practical and academic literature and in particular from interviews with experts. A focus group discussion was used to check the practicability of the model. The new model represents a universal BI / big data analytics reference model. It can be seen as a guideline for companies, who can evaluate their existing architecture with the aim of improving their SSBI or big data analytics capabilities. It takes different user groups and their different demands into account in a BI/big data analytics architecture. Collaboration rooms and a (self-learning) knowledge database are presented as additional supporting elements. Discussions with practitioners have shown that these elements have great potential to support SSBI because they make implicit knowledge of BI users usable. In further research the applicability should be reviewed by various companies.

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