DESIGN FACTORS FOR SERVICE-ORIENTED ARCHITECTURE APPLIED TO ANALYTICAL INFORMATION SYSTEMS: AN EXPLORATIVE ANALYSIS

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Abstract

Today's analytical information systems demand innovative architecture concepts in order to address requirements like flexibility and faster time-to-market. Service-oriented architectures (SOA) as a current trend might meet these challenges. So-called BISOA describes the approach of deploying SOA in Business Intelligence systems. We identified two research questions aiming at finding insights about the interdependencies of BISOA and the organization's system landscape: What are the dominant design factors of BISOA and what are the distinct realization approaches of BISOA? The paper answers the questions by means of empirical research. Besides the factor describing the degree of BISOA realization, three further design factors resulted from the analysis: excellence in embedded Business Intelligence (BI), process orientation, and excellence in data management. Depending on the factors distinct approaches of real-world organizations to deploy SOA in BI systems were derived. These profiles allow us to gain insight which aspects have to be considered besides mainly technical oriented implementation issues for BISOA. Surprisingly, there does not exist such a strong correlation between BISOA and operational BI as often assumed.

Keywords: Business Intelligence (BI), service-oriented architecture (SOA), operational BI, empirical analysis.

1 INTRODUCTION

Service-oriented architecture (SOA) dominates as a recent trend the discussion about today's IT architectures. It is currently establishing as an accepted and useful concept for information system architectures in organizations (Baskerville et al., 2005; Krafzig et al., 2005; Schelp & Winter, 2007). Organizations are faced with major challenges in order to adapt fast changing organizational structures in a flexible way and to support new or modified business processes. The challenges encompass not only business aspects but also technical issues such as reducing complexity of the application landscape. Service-oriented architectures are aimed at providing support in this context.

On the other side, analytical information systems represent meanwhile an essential component of the enterprise application landscape. Business intelligence (BI) as the underlying concept is used as an umbrella term to describe the processes and systems dedicated to the systematic and purposeful analysis of an organization and its competitive environment. Also analytical information systems demand increasingly innovative architecture concepts in order to address new challenges like realizing operational BI approaches (cf. Section 2.2). Furthermore, organizational units responsible for development and operations of analytical information systems have to assess if the SOA paradigm might apply to analytical information systems as well and have to design a possible integration of

SOA in the current architecture landscape. In the following, we designate the term “BISOA” to the situation that SOA is applied to analytical information systems and BI systems, respectively.

According to a survey of Ventana Research about the status of SOA in BI, only 33% of organizations reported they believe their internal IT personnel have the knowledge and skills to implement BI services (Everett, 2006). However, the decision, if and how to apply BISOA and to develop an appropriate procedure model requires know how about the interdependencies between BISOA and the current system landscape.

We have reviewed both scientific and practitioner oriented publications in order to assess the state-of-the-art of BISOA. Whilst there are numerous articles published by consultancies, research and advisory firms, and software vendors, only little work can be attributed to the scientific community. The paper at hand aims at providing insights to the aforementioned interdependencies, based on the results of an empirical analysis. Moreover, it tends to assist the selection and adaptation of frameworks from information systems research, which may support the introduction of BISOA concepts in organizations. In the past, design research artefacts including models and methods were rather generic and did not differentiate enterprise specific needs. Thus, concepts in design research have evolved which aim at enhancing generic problem solving approaches such as adaptable conceptual models (vom Brocke, 2007; vom Brocke & Buddendick, 2006) or situational method engineering (Becker et al., 2007; Ralyté & Rolland, 2001). By means of these approaches, existing models and methods can be refined to ensure that a model or method fits better to problem-specific requirements than a generic one does. The study at hand investigates relevant design factors, which influence the application of relevant design research artefacts (methods or methods fragments of e.g. a BISOA introduction). In addition, it tends to reveal BISOA profiles these artefacts are applied for. Consequently, the following two research questions will be discussed:

1. What design factors dominate the realization of BISOA?
2. Based on these design factors: Which distinct approaches to BISOA are pursued by real-world organizations?

The remainder of the paper is organized as follows: Section 2 provides an overview of SOA and its deployment in analytical information systems (“BISOA”), respectively. In Section 3 the empirical investigation for identifying design factors as well as BISOA approaches using data collected from a written survey is described. Following, Section 4 discusses an interpretation and discussion of the survey results. Section 5 concludes and provides an outlook on further research.

2 THE CONCEPT OF SOA AND BISOA

2.1 The SOA paradigm

The main idea of SOA is to encapsulate business functionality into small loosely coupled services, which – once implemented on a software level – may be flexibly orchestrated to match the particular and ever changing business requirements (Krafzig et al., 2005). Consequently, rather than providing a technical solution, the SOA concept presents a business driven architecture paradigm. SOA aims at designing an ideal IT architecture, which is not built by monolithic applications but by standardized components (services) that are designed according to underlying business functionalities.

Many expectations concerning various and extensive benefits come along with the service-oriented paradigm, in particular addressing the need for improvement of existing IT architectures. The main benefits of SOA are amongst others:

Increased reuse rate: Many business functionalities that are realized in software are reused in various business processes. By means of SOA these software functionalities can be used by several processes via standardized interfaces. Consequently, redundant development can be avoided (Endrei et al., 2004).

Reduction of complexity: SOA facilitates the decoupling of business process control from the technical functionality. The coordination mechanisms are shifted to an integration layer and are therefore separated from the functional components. In addition, the interface standardization allows a reduction of the number of interfaces.

Increased manageability: Several applications might simultaneously benefit from further development of services – assumed an appropriate version management has been established. As the service functionalities are encapsulated via interfaces the underlying software might be (ex)changed without requiring adaptations in the corresponding components.

Faster time to market: Due to more efficient deployment mechanisms SOA enables the IT departments to react faster to changing business requirements. Consequently, agility and flexibility are enhanced (Bieberstein et al., 2005; Schelp & Winter, 2007).

Evolutionary extensibility, cost savings, investment protection, and outsourcing potentials are considered as further advantages. A detailed discussion about SOA can be found e.g. in (Endrei et al., 2004; Krafzig et al., 2005; Keen et al., 2004).

2.2 SOA for BI systems (BISOA)

The aforementioned Ventana Research survey confirmed the relevance of BISOA. More than 81% of respondents said SOA was important to BI due to its powerful combination of business and IT benefits. From the business side, nearly 50% felt that BI services would help make information more broadly available, while also improving the business's ability to respond faster to change. From the IT side, nearly 66% felt that BI services would help IT departments to respond to business needs in a better way, with another 33% viewing ease of integration and lower lifecycle management costs as key benefits (Besemer, 2007). These benefits are similar to the generic SOA advantages as presented in Section 2.1.

BI systems can act either as service provider or as service consumer. In addition, functionalities within BI systems can be realized via services. Nowadays, there is a (more or less) common understanding which services can be differentiated in BI systems / architecture, although classification criteria, terminology, and the service types in details still vary (Besemer, 2007; Gordon et al., 2006; Martin & Nussdorfer, 2007; Wu et al., 2007). The most popular service types are given below:

Sourcing (Backend) services: Operational data sources are connected to the data warehouse via dedicated extraction services or via already existing services provided by operational applications (Gordon et al., 2006; Keith et al., 2007).

Transformation services: Transformation functionality within ETL (extraction, transformation, loading) processes is realized by means of services. Examples are aggregations, encoding, etc. (Gordon et al., 2006; Wu et al., 2007).

Analytical (Frontend) services: BI data and products are made available to end users and other applications via services. An overview of analytical services like reporting, dashboard, alerting services can be found amongst others in (Gordon et al. 2006; Martin 2006; Martin & Nussdorfer 2007).

Infrastructure services: Tasks with infrastructure character such as meta data, master data, and data quality functionalities are realized by means of services (Gordon et al., 2006).

In addition to these use cases, which correspond to the typical data warehouse architecture layers, operational BI is often mentioned as an application area for BISOA, e.g. in Besemer (Besemer 2007; Blasum 2006; Eckerson 2007; Keny & Chemburkar 2006). There is not yet a common understanding about the term operational BI. Some authors focus on specific aspects, others like Eckerson (2007), consider operational BI as an umbrella term: “Operational BI delivers information and insights to a broad range of users within hours or minutes for the purpose of managing or optimizing operational or time-sensitive business processes“. Eckerson (2007) presents a survey conducted about operational BI. Respondents being asked amongst others for main challenges in deploying operational BI, rated “Architecting the system” to the top. Moreover, other authors point out the significance of SOA to near/real time data delivery (data warehousing) (Abrahiem, 2007; Wu et al., 2007).

Considering the various fields of applications for SOA in analytical information systems mentioned above and driven by the demand for innovative BI architecture concepts, it seems worth the effort to consider BISOA as an alternative or enhancement of established architectures. In the next section we will elaborate the predominant design factors and analyze their impact on the realization degree of BISOA.

3 EXPLORATIVE ANALYSIS

3.1 Research method

Explorative analysis was used as the underlying research method. By means of a factor analysis we identified the predominant design factors (indicators) for BISOA realization. This method is used in order to extract a small number of relevant mutually independent factors from a multiplicity of variables (of a data set) (Härdle & Simar, 2003). In the field of factor analysis two different approaches with different goals can be distinguished: confirmatory factor analysis (CFA) and exploratory factor analysis (EFA) (Thompson, 2004). A CFA approach requires “a firm a priori sense, based on past evidence and theory, of the number of factors that exist in the data, of which indicators are related to which factors, and so forth” (Brown, 2006). In contrast to that, researchers using the EFA approach may not have any specific expectations regarding the number of underlying factors. The explorative nature of the article at hand implicates therefore the application of EFA.

A cluster analysis of the extracted factors was then performed in order to identify different BISOA approaches. Clustering as a combinatorial data analysis technique investigates “a set of objects in order to establish whether or not they fall […] into groups […] of objects with the property that objects in the same group are similar to one another and different from objects in other groups” (Gordon, 1996). Initially, these groups are unknown and need to be determined. Various clustering methods for different purposes are available. They can be categorized by the types of algorithm used to obtain the clusters. Most important clustering techniques include agglomerative, divisive, incremental, direct optimization, and parallel algorithms (Gordon, 1996). According to Härdle & Simar (2003) agglomerative algorithms have the largest significance in practice. Thus the clustering method of the paper at hand is based on such an algorithm. Starting with n clusters, each containing a single object, an agglomerative algorithm reduces the number of clusters by merging the two most similar ones at each step. In our context, the cluster analysis aimed at determining the correlations between the indicators (reflecting the design factors) and BISOA approaches in organizations and consequently, at evaluating the relevance of these indicators.

3.2 Data collection and selection

Data for the empirical analysis was collected by means of a written survey that was conducted at a practitioner conference on data warehousing and business intelligence held in Switzerland. The conference was attended by 137 specialists and executives with primarily large and medium-sized companies in the German-speaking area. The questionnaire used for the survey was designed to answer the research questions (cf. Section 1), i.e. to assess design factors for BISOA and to identify BISOA approaches. Prior to the survey, the questionnaire was revised by experts from both the scientific community and the entrepreneurial world in terms of completeness and comprehensibility.

The items of the questionnaire cover a broad range of layers relevant to the context of BISOA (cf. Section 3.3). The respondents were asked to indicate their agreement with several statements on a five-tiered Likert scale (0 to 4) from the perspective of the organization they are working for. There was a dedicated time slot during the event to fill in the questionnaire. The objectives, structure, and terminology used in the written survey were explained to the attendees. A total of 68 questionnaires were returned. This corresponds to a return rate of approximately 49.6%. If a data set was incomplete (11 questionnaires) or apparently inconsistent (checked by control questions; 6 questionnaires), the questionnaire was discarded. Fifty-one duly completed questionnaires were used as foundation for the analysis, resulting in an overall return rate of about 37.2%. The data set is considered to constitute an adequate basis for an explorative analysis.

Respondents of the survey were employees from organizations in the German-speaking area. Large and medium-sized organizations accounted for the largest share: 23.5% of all organizations have 1000-5000 employees, 36.5% more than 5000 employees. In particular the industry sectors banking (22.0%), insurance (11.8%), and retail (8.8%) were mainly represented.

3.3 Description of the data set

For the purpose of information system analysis in organizations frameworks, differentiating several layers, are often used in order to facilitate a transparent overview of complex correlations between information systems and objects, respectively (e.g. processes) (Alter, 2004; Winter & Fischer, 2007; Zachman, 1987). The deployment of BISOA affects several levels in such frameworks. Therefore, the questionnaire of the empirical analysis incorporated with regards to its content and structure all layers being relevant in this context, namely process level, integration level, and application level.

The process level, which is addressed by all approaches of aforementioned authors, includes all processes along the organization's value chain. That level was covered in the questionnaire by asking e.g. about the definition of process output and process owners. The application layer, also part of the aforementioned models, subsumes all software artefacts like software services and data structures. The questionnaire addressed this level by primarily technical questions, e.g. about functionality or usage of analytical information systems (Wixom et al., 2008). Finally, the integration layer according to (Winter & Fischer, 2007), links the process layer and the application layer and enables the integration of software components and processes. Considering this layer, questions also addressed integration options of business processes and BI applications, such as support of process execution through analytical information or process monitoring (Kueng, 1999) or interface configuration. In addition to questions focusing on these three layers, statements were asked describing the degree of BISOA realization – in order to derive the corresponding correlations.

3.4 Factor analysis

As stated above, the factor analysis method of this empirical research is based on EFA (cf. section 3.1) in order to identify the predominant design factors for BISOA (cf. research question 1 in Section 1). The overall objective is to find a common term embracing multiple items. The input for the factor analysis comprised of 15 items. Prior to the EFA, the adequacy of the data set is verified using two criteria. Variables (items) are suitable for factor analysis, if and only if the anti-image of the variables is as low as possible. In such a case the off-diagonal elements of the anti-image covariance (AIC) matrix are as close as possible to zero. As suggested by (Dziuban & Shirkey, 1974) a correlation matrix can be seen as unsuitable for factor analysis, if the percentage of the off-diagonal elements unequal to zero (> 0.09) in the AIC matrix is 25 % or more. The criterion of the data set at hand is about 18.5%.

As second verification criterion the measure of sampling adequacy (MSA), proposed by (Kaiser & Rice, 1974), can be applied. MSA represents an indicator for the extent, to which the input variables belong together, and therefore provides information on whether a factor analysis can reasonably be performed or not. Kaiser and Rice (1974) appraise a value of 0.7 or more as “middling”, i.e. the data set is considered to be appropriate for applying factor analysis techniques (Kaiser & Rice, 1974). According to (Kaiser & Rice, 1974) a value of 0.7 is to be seen as average and 0.8 as good. In the present case the value is 0.802 which justifies the data set as suitable for the factor analysis.

Within the fields of factor analysis two main techniques can be distinguished – the principal components and principal axes factors analyses, which can be counted by far to the most commonly used factor extraction methods (Thompson, 2004). The higher the number of variables of the data set the more similar the results of principal components and principal axes factor analyses will be (Ogasawara, 2000). According to (Thompson, 2004) principal components analysis (PCA) has some additional preferable properties and is probably the most frequently used EFA extraction method for empirical studies. Thus, PCA is used as factor extraction method in the paper at hand. In order to determine the desirable number of factors, two statistical verification methods are applied, the Kaiser-Guttmann criterion and the scree test. According to the Kaiser-Guttmann criterion (Guttman, 1954; Kaiser & Dickman, 1959) the number of factors to be extracted should equal the number of factors with eigenvalues larger than 1 (cf. Table 1). This results in the extraction of four factors explaining 72.3% of the total variance. The scree plot points to the same solution.

Factor	Total	% of Variance	Cumulative %
1	6.521	43.474	43.474
2	1.899	12.662	56.136
3	1.349	8.993	65.130
4	1.071	7.142	72.272
5	0.750	5.001	77.273
6	0.634	4.224	81.497
7	0.556	3.707	85.203
8	0.491	3.274	88.478

Factor	Total	% of Variance	Cumulative %
9	0.404	2.694	91.172
10	0.330	2.200	93.372
11	0.275	1.836	95.208
12	0.257	1.710	96.918
13	0.193	1.284	98.202
14	0.166	1.110	99.311
15	0.103	0.689	100.000

Table 1. Eigenvalues

As final step the nature of the underlying constructs has been clarified by applying the Varimax method as the most common factor rotation method with Kaiser normalization (Thompson, 2004). The rotated component matrix is depicted in Table 2. Items are assigned to a factor if the factor loading adds up to at least 0.5 (Härdle & Simar, 2003). The four factors vary in the number of items with a range from three to four items.

Item description	Factor 1	Factor 2	Factor 3	Factor 4
Dedicated projects aiming at deploying SOA in BI projects.	0.843	0.083	0.193	0.252
SOA is deployed (selectively) in the context of upcoming BI projects.	0.833	0.164	0.125	0.028
Know how regarding the deployment of SOA in BI systems is acquired.	0.794	0.199	0.222	0.066
Service-oriented architectures are applied to operational systems.	0.745	0.071	-0.036	0.292
Analytical information is used for automatic process execution.	0.310	0.845	0.064	0.144
Analytical information supports the execution of business processes.	0.043	0.796	0.272	0.063
Analytical information and process information are combined and jointly interpreted.	0.203	0.749	0.110	0.366
For all relevant business processes all relevant performance indicators are measured.	0.046	0.622	0.384	0.334
All activities and their dependencies are defined for all relevant business processes.	0.159	0.195	0.852	0.215
Process output is defined for all relevant business processes.	0.170	0.134	0.834	0.237
Process owners are defined for all relevant business processes.	0.111	0.205	0.725	0.201

Item description	Factor 1	Factor 2	Factor 3	Factor 4
There exists a mature master data management.	0.174	0.044	0.189	0.790
There exists a mature data quality management for BI systems.	0.233	0.349	0.123	0.758
There exists a mature meta data management for BI systems.	0.088	0.226	0.422	0.650
There exists a mature data ownership concept.	0.183	0.266	0.305	0.635

Table 2. Results of factor analysis (rotated component matrix)

The following paragraphs discuss the identified factors and give a short interpretation for every factor.

Factor 1: Excellence in BISOA

Four items were found to have significant impact on the first factor. Their common denominators are maturity aspects of BISOA realization in organizations. According to our analysis, there are four indicators for the achievement of excellence in BISOA: First, dedicated projects aiming at deploying SOA in BI projects, second SOA is (selectively) deployed in the context of upcoming projects, third, know how of introducing SOA concepts into BI system architectures, and forth, SOA usage degree within operational systems. The last indicator seems to be obvious since in most organizations BISOA will probably not be addressed independently of other SOA activities. Ideally all (BI)SOA activities are synchronized to achieve synergy effects.

Factor 2: Excellence in embedded BI

The second factor is made up by four items that essentially account for embedded BI, also called "composite applications" in (Eckerson, 2007). Our findings suggest that the level of excellence in embedded BI depends on the usage of analytical information for automatic process execution and the support of analytical information for the execution of business processes. In addition, excellence in embedded BI is positively influenced by the degree of the combination of analytical information and process information. The degree of the measurement of relevant performance indicators for relevant business processes has impact on this factor as well. Especially the first three items are similar to the understanding of operational BI (i.e. the integration of BI and business process management), as described e.g. in (Marjanovic, 2007). Eckerson (2007) (cf. Section 2.2) differentiates several levels of operational BI. The variables loading on the second factor correspond to one of these levels: "facilitate processes" by embedding BI into operational applications.

Factor 3: Process orientation

Three items exhibit high loadings on the third factor. In summary, they can be characterized by the term "process orientation". All variables describe relevant preconditions for alignment of business activities to business processes: All activities and their dependencies as well as process output and process owners are defined for all relevant business processes.

Factor 4: Excellence in data management

Finally, four items covering relevant data management aspects were found to have substantial positive impact on the fourth factor, namely master data management, data quality management, meta data management, and data ownership concept.

3.5 Cluster analysis

In order to identify distinct realization approaches of BISOA, cluster analysis was applied on the data set using the calculated factor values of the four previously identified factors as input data. The Ward algorithm and the squared Euclidean distance have been used as fusion algorithm and distance measure, respectively. In literature the Ward algorithm is recognized as an efficient partitioning mechanism (it reveals the appropriate number of clusters with a similar number of observations in each cluster at the same time) generating good clustering results (Hair Jr et al., 2006; Ward Jr, 1963).

Thus, it is applied in the study at hand. Starting with individual cases each representing a single cluster Ward's method continues by combining them into clusters until each and every case belongs to the same cluster. For determining which clusters have to be merged next, the sum of the squared Euclidean distance between each case and the mean of its cluster is minimized. While also other clustering algorithms and distance measures have been tested best results in terms of interpretability, context, and purpose of the study at hand could be realized by means of the Ward method in combination with the squared Euclidean distance. The so-called dendrogram (cf. Figure 1) provides a visualization of the hierarchical clustering process. By means of the dendrogram the number of clusters to be built for a particular clustering problem can be graphically derived. In the context of the study at hand this heuristic suggests that the construction of four clusters (representing four distinct realization approaches of BISOA) is the most reasonable solution, marked in the dendrogram between the two dotted lines.

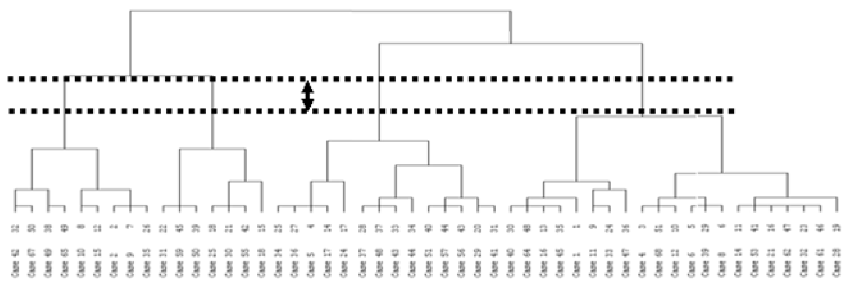

Figure 1. Results of cluster analysis (dendrogram)

Table 3 exhibits the arithmetic means and the standard deviations of the four calculated factor values of the four clusters. A graphical representation of the arithmetic means is added in form of pie charts (please note: the pie charts are representing relative, not absolute values).

	Excellence BISOA			Excellence embedded BI			Process orientation			Excellence data mgt.		
	Arithmetic mean		Standard deviation	Arithmetic mean		Standard deviation	Arithmetic mean		Standard deviation	Arithmetic mean		Standard deviation
Cluster 1	●	0.76	0.66	◕	0.30	0.70	◑	-0.13	0.87	●	0.73	0.72
Cluster 2	●	0.67	0.99	○	-1.05	0.89	●	1.05	0.71	◔	-0.74	0.54
Cluster 3	◔	-0.61	0.79	●	0.66	0.94	◑	-0.32	0.79	◔	-0.44	0.69
Cluster 4	◔	-0.74	0.68	○	-1.42	1.27	◔	-0.73	0.87	◕	0.10	0.51

Table 3. Results of cluster analysis (arithmetic means and standard deviations of factor scores for each cluster)

Based on this information, the clusters can be characterized as follows:

Cluster 1: Data management experts

Those 21 organizations (i.e. the majority of all respondents) that are grouped into the first cluster are characterized by the most advanced degree of BISOA realization and by high levels of excellence in data management but by average level of excellence in embedded BI and of process orientation. These results correspond e.g. to (Gordon et al., 2006) who claim data management aspects like data ownership, enterprise data, etc. as critical success factors for BISOA.

Cluster 2: Process orientation experts

The second cluster is made up of 9 organizations. Although the cluster is characterized by nearly the same degree of BISOA realization as the first cluster, the remaining design factors differ significantly. In contrast to the first cluster these organizations exhibit a high level of process orientation but low levels of embedded BI and data management.

Cluster 3: Embedded BI experts

The third cluster merges 14 organizations that are characterized by a low degree of BISOA realization, but the highest excellence level of embedded BI. On the other hand the maturity level regarding data management and process orientation is rather low.

Cluster 4: Freshmen

Nine organizations where embedded BI and process orientation get the lowest attention in comparison to the other clusters are grouped in this cluster, which is characterized by the lowest degree of BISOA realization. The maturity level of data management is on average.

According to the values determined in the cluster analysis, the four realization approaches to BISOA can be arranged in a two-dimensional matrix (cf. Figure 2). "Excellence in data management" (factor 4) is being depicted on the horizontal axis and "Excellence in BISOA realization" (factor 2) is being displayed on the vertical axis. For both dimensions, high and low parameters (i.e. high and low levels of implementation) are distinguished for clarity. Thus, the classification scheme resembles a 2x2 matrix. Within each of the four segments, we furthermore differentiate between the "Process orientation (factor 3, horizontal axis) and "Excellence in embedded BI" (factor 2, vertical axis). Cluster 4 ("Freshmen") might also be assigned to the lower left side of the matrix as its maturity level of data management represents an average value, which cannot be clearly allocated to high or low values.

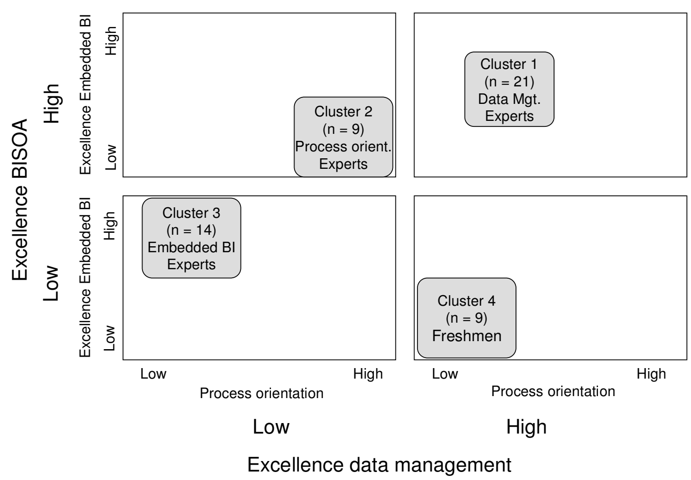

Figure 2. Realization approaches of BISOA

4 DISCUSSION AND INTERPRETATION OF RESULTS

We have identified four relevant BISOA profiles in Section 3. In the following, two aspects regarding the results of the empirical analysis and the cluster analysis will be discussed in detail. Further interpretation of the results might be useful and interesting.

Improvement of the BISOA maturity

Figure 2 illustrates the fragmentation of surveyed organizations into two main groups: One group is characterized by a high degree of BISOA realization and the second group by a low degree, respectively. However, within these groups there is no homogeneity concerning the maturity levels of the remaining (design) factors. Obviously, there is no single and definite approach to deploy BISOA or to increase BISOA maturity levels, respectively. According to the analysis results, a high BISOA maturity level corresponds either to excellence in data management or to a high degree of process orientation. There are no organizations (at least among the respondents) that are characterized by high maturity levels of both, data management and process orientation, or even of all three factors (including embedded BI).

In the survey we also asked to indicate the same statements for the future. These values are not in the focus of the paper at hand and of the empirical analysis presented so far. However it is evident that nearly all organizations aim at improving the degree of BISOA realization. This is also true for organizations with a high degree of BISOA realization in the cluster analysis (cluster 1 and cluster 2). This might be explained by the reason that these factor values have to be regarded as relative, not absolute. I.e., even organizations belonging to cluster 1 and 2 do not realize a true mature level of BISOA so far. According to the analysis results it might be concluded that activities to increase the degree of BISOA realization might be positively influenced by simultaneous improvement of the remaining (design) factors (data management, process orientation, and embedded BI). Regarding the fact that very few organizations are characterized by mature levels of all three "dimensions" (factors), it seems that organizations with comparatively mature BISOA (cluster 1 and cluster 2) still have significant potential for further improvement regarding BISOA.

Relevance of BISOA for operational BI scenarios

As mentioned in Section 2.2 many authors link SOA with operational BI and praise operational BI as the main use case for BISOA. The analysis results have revealed that this coherence cannot be seen as evident as it is often claimed. At least regarding the facets of embedded BI / composite applications – according to (Eckerson, 2007) one stage in operational BI - do not correlate unambiguously to BISOA. In cluster 1 and cluster 2, which include organizations with a comparatively high mature BISOA approach, both enterprises types, with an advanced degree of embedded BI and with a low degree, have been found. Accordingly, the same situation can be observed in cluster 3 and cluster 4 (organization with a comparatively low mature BISOA approach). Thus, BISOA does not necessarily constitute one or even the only driver for operational BI and vice versa. At least it seems that coherence and interdependencies between BISOA and operational BI are not as straight and definite as often assumed, especially in practice. In fact, other factors also have impact, namely the degree of process orientation and the maturity of data management, as the study at hand has shown. One-track argumentation regarding BISOA and operational BI and significant correlations in-between should consequently be seen more carefully, at least if any coherencies are only assumed and not somehow proved.

5 SUMMARY AND OUTLOOK ON FUTURE WORK

Deploying the SOA paradigm to analytical information systems, promises progress in realizing the vision of closed action loops between operational systems and analytical information systems. However, BISOA so far is not addressed extensively by scientific community. Consequently, we identified two research questions aiming at finding insights about the interdependencies of BISOA and an organization's system landscape. A factor analysis and a cluster analysis were applied in order to identify predominant design factors for BISOA in an explorative way. We also determined typical scenarios for BISOA and explored the impact of relevant EA layers on the shaping of those scenarios.

The resulting design factors might support the application of models and methods in information systems research for organizations that are planning or currently realizing BISOA. The factors represent dimensions in which BISOA profiles differ from each other. As mentioned in Section 4, approaches for BISOA deployment vary in the surveyed organizations. Thus, models and methods that tend to support the deployment phase should be adaptable in order to address the design factors and different maturity levels ("BISOA profiles") elaborated in the study at hand. For instance, data management as an essential aspect should be incorporated in a method while considering the specific maturity level of data management in the organization.

Moreover, the design factors can serve as a guideline and provide recommendations for actions. Due to their identified impact on the maturity level of BISOA, they clarify which issues should be addressed in addition to the usually technical dominated implementation aspects of BISOA. In other words, it is not recommended to regard BISOA as an isolated IT project – indeed, the coherencies to other aspects (represented by the design factors) should be considered carefully.

Surprisingly, the cluster analysis depicted that correlations between BISOA and operational BI (at least when focussing on the facet of embedded BI) are not as evident as often supposed. It seems that additional factors influence BISOA simultaneously.

The analysis results might serve as the basis for further research. On the one hand, it seems worth to further detail the scenarios and to elaborate their characteristics. Possible development paths for BISOA and more detailed recommendations may result in a comprehensive procedure model and a maturity model, respectively. On the other hand, as already mentioned, in the survey the respondents were also asked about their assessments for the future. Since this information is not included in the empirical analysis so far, further research might generate new interesting insights. Finally, the survey might be expanded to further organizations in order to put the empirical analysis on a firmer footing.

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