IN-MEMORY TECHNOLOGY AND THE AGILITY OF BUSINESS INTELLIGENCE – A CASE STUDY AT A GERMAN SPORTSWEAR COMPANY

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Abstract

The retail industry has changed significantly due to altered shopping behavior of customers and technological advancements in recent years. This enforces organizations to quickly adapt to these dynamically evolving circumstances. Most of the major organizations utilize Business intelligence (BI) to support their corporate strategies. Therefore, the adaptability of BI gained increasing importance in theory and industry practice over the last years. Agility is particularly challenging in the domain of BI since the underlying architecture of enterprise-wide decision support with data warehouse (DWH)-based BI is not built upon agility, but on reliability and robustness. Although the usage of agile project approaches like Scrum has been explored, there is still a lack of research investigating further effects on BI agility. Hence, we analyzed whether the characteristics of DWH and BI impact the agility of BI in an in-depth case study at a globally operating German sportswear designer and manufacturer. In particular, we want to identify if a technology like in-memory can help to achieve more BI agility. The findings indicate that IM technology acts as a technology enabler for agile BI. The impact of some DWH characteristics on BI agility is significantly positively influenced if IM technology is used.

Keywords: Business Intelligence, Agility, In-Memory Database, Case Study.

1 INTRODUCTION AND MOTIVATION

The empowerment of the consumer by using emerging technologies altered the retail industry dramatically in recent years. For instance, customers use smartphones to compare prices while shopping in stores or base their buying decisions on feedbacks via social media platforms. Additionally, an ever-growing list of online retailers offer to deliver products with competitive prices directly to the customers (MacKenzie et al. 2013). Market research (Davison and Burt 2014; MacKenzie et al. 2013; Mulpuru et al. 2014) indicates that these business and technology trends completely change retail as we know it today. Some of these industry observers even predict more changes in the next few years than there were over the past century. Thus, retail organizations need to quickly adapt to this dynamically changing environment in order to stay successful. Managers and decision makers of retail companies must be able to promptly answer questions like where to sell products (large or small stores and/or online) or how to react to different pricings of competitors. They need to operate and adapt their multichannel strategies flexibly and gain insights from huge amount of customer or social media data frequently.

Hence, fact-based decision making on a broad and reliable data basis and being prepared for multiple scenarios is one of the most obvious approaches. Decision making as well as the execution of business processes is usually supported by information systems (IS). Business intelligence (BI), as a distinct class of dispositive IS, is used as an instrument to understand and gain insights from internal and external information and the top priorities of CIOs in 2014 (Schulte et al. 2013). Primarily utilized to reflect an operational performance (reporting-centric), organizations tend to use BI more and more to actively steer the future. Therefore, a quick adoption is crucial to support timely decision making for retailers as described above. But, achieving agility is particularly challenging in the domain of BI (Moss 2009). The vision for BI has traditionally been a single, central repository of data that supports operational and analytical functions for the entire organization. So the tasks of reporting and consolidation typically have rigid requirements in terms of robustness, reliability, and non-volatility of the data provided by the system (Inmon 1996). On the other hand, BI needs to adjust to changing situations and must collect an enormous amount of data of the surrounding environment (Chen et al. 2012; Gartner 2011; Redman 2008). Many organizations utilize a data warehouse (DWH) as the basic concept for BI. As a DWH is rather static by design the question remains how BI can be adopted faster and therefore behave in a more agile way. Although the usage of agile project approaches like Scrum (Schwaber 1997) has been explored, there is still a lack of research investigating further effects on BI agility. Such effects may be achieved by different architectural approaches (Caruso 2011), adequate organizational structures and processes (Zimmer et al. 2012) or technologies such as in-memory (IM) (Evelson 2011). Current research activities identified positive impacts of in-memory databases (IMDB) on BI (Knabke et al. 2014; Knabke and Olbrich 2011; Plattner 2009; Plattner and Zeier 2011). But, the impact of IMDB on the agility of BI has not been sufficiently investigated and mostly promoted by software vendors. Thus, the aim of this paper is to investigate if and how the usage of IMDB affects the adaptability of BI. Therefore, we conducted a case study at a globally operating German sportswear designer and manufacturer who implemented an architectural switch from disk-based databases (DRDB) to IMDB. To accompany that project, we address the following research questions:

- Do requirements of BI agility negatively interact with the common DWH-based BI approach?
- Does the usage of IM technology affect the agility of BI at the surveyed organization?

To achieve a common theoretical foundation we first give a background on DHW-based BI and IMDB and highlight the value of agility in the context of BI. Afterwards, we introduce our research approach and the case study setting. The fourth section explains the data collection process in detail. Next, we present the results of our study and their interpretation before considering its limitations. In the last section, we describe our contribution as well as an outlook to future research opportunities.

2 THEORETICAL FOUNDATION

2.1 Data Warehouse-based BI and In-Memory Databases

BI can be defined as "a broad category of applications, technologies, and processes for gathering, storing, accessing, and analyzing data to help business users make better decisions" (Watson 2009). It is an umbrella term for systems and processes that turn raw data into useful information (Chen and Siau 2012; Wixom and Watson 2010). Most multidimensional BI systems, particularly in organizations with several source systems, utilize the DWH approach to systematically extract, harmonize and provide data to reflect the organization's single point of truth (Kimball and Ross 2002; Rifaie et al. 2008; Watson 2009; Watson and Wixom 2007). A DWH is built to fulfill fundamental requirements (Inmon 1996), i.e. integration, subject-orientation, time-variance and non-volatility. It usually consists of several layers that physically store data if based on DRDB. Data is extracted from source systems, transformed and loaded into the DWH. This process is called ETL-process (extract, transform and load). The data is further cleansed, harmonized and consolidated inside the DWH as single source of truth of an enterprise. To meet application-specific requirements the "general" data can be enriched with business logic before made available for analysis and reporting. Data is usually aggregated DWHs based on DRDB to meet performance and response time requirements during analysis operations (Knabke and Olbrich 2011). In addition, many BI tools use a de-normalized approach (e.g. star schema) (Kimball 1996) which allows for efficient read operations on big data volumes.

Although data can be cached in the main memory of a DRDB system, it needs to be processed and stored in several layers and the primary storage location remains a magnetic hard disk. Instead, an IMDB keeps its data permanently in main memory of the underlying hardware. Main memory is directly accessible by the CPU(s) and the access is orders of magnitudes faster (Garcia-Molina and Salem 1992). Due to recent price reductions for main memory and the usage of dedicated compression techniques it is now possible to even hold the entire data of large-size companies in-memory (Plattner and Zeier 2011). IMDB-based BI infrastructures use column-oriented data storage to optimally support online analytical processing (OLAP) applications like BI. Column-oriented storage also allows for better suited compression techniques and gains huge performance impacts – up to factor 1000 with real-life data (Plattner 2009).

2.2 Agility and its Value for BI

The idea of organizational agility has been established in practice and discussed in literature for decades and is not limited to IS. It originated from the field of manufacturing (Pankaj et al. 2009; van Oosterhout et al. 2007) and has also been used for several years in different management areas, such as corporate performance management or supply chain management. In business literature, it drew mainstream attention through the work of Goldman et al. (1991) with regard to "agile manufacturing". Nevertheless, the definition of agility is ambivalent in scientific literature and industry (McCoy and Plummer 2006; van Oosterhout et al. 2007). While the term "agile" is described as the ability "*to move quickly and easily*" by Oxford Advanced Learner's Dictionary (Hornby and Cowie 1989, p. 23), researchers have provided a wide range of definitions, often with deficiencies in the academic approach to arrive at these definitions (Pankaj et al. 2009). In contrast, Conboy and Fitzgerald (Conboy and Fitzgerald 2004b) conducted a cross-discipline literature review to derive a holistic definition of agility. In particular, they investigated the underlying concepts of agility, i.e. flexibility and leanness (Conboy 2009; Sharifi and Zhang 1999; Towill and Christopher 2002). They define agility as "*the continual readiness of an entity to rapidly or inherently, proactively or reactively, embrace change, through high quality, simplistic, economical components and relationships with its environment*" (Conboy and Fitzgerald 2004a, p. 110). This definition is in line with the definition of Pankaj et al. (Pankaj et al. 2009) who stated that agility must respect the abilities to sense a change, diagnose a change as well as select and execute a response to a change in real-time. However, real-time does not necessarily mean a very short amount of time, e.g. seconds. Instead, the actual physical length of time is dependent on the context of the IS and may differ for strategic, tactical and operational IS (Marjanovic 2007; White 2005) as they support business processes of different time frames. For instance, the time frame for strategic processes may range from months to years (Pankaj et al. 2009).

To get an understanding of agility in a BI context, we follow the framework suggested by Knabke and Olbrich (2013). We believe this framework suits our research very well as the authors analyzed the concept of agility in IS in a structured literature review and mapped their findings to the domain of BI. As a result of their analysis they grouped similar constructs of BI agility as illustrated in Figure 1. These agility dimensions are briefly explained in the following:

Change Behavior is a central construct of agility and describes the behavior of BI with regard to change. Thus, a system can behave reactively, proactively, create or even learn from change.

Perceived Customer Value (PCV) highlights the importance of quality, simplicity and economy as values for the customer of BI.

Time describes the ability of BI to adapt to changing environments over time. This can either happen in a continuous process or on an “ad-hoc” basis. The actual physical length of time is dependent on the context of the IS and may differ for strategic, tactical and operational IS.

Process comprises the ability of BI to sense, analyze and respond to a change. Agile BI should support methodologies and organizational structures to be able to quickly respond to changing requirements.

Model incorporates the architecture of BI. Agile BI may even require a new architectural approach which is among others, reusable, reconfigurable and scalable.

Approach describes the process method that is used in BI projects, e.g. traditional models such as waterfall models or agile methods like Scrum.

Technology considers the underlying technology of BI. This may e.g. be a DRDB or an IMDB.

Environment of BI can be interpreted in multiple ways such as business processes, people, customers, clients, or formalities. It respects the fact that the need for change often arises outside the IS.

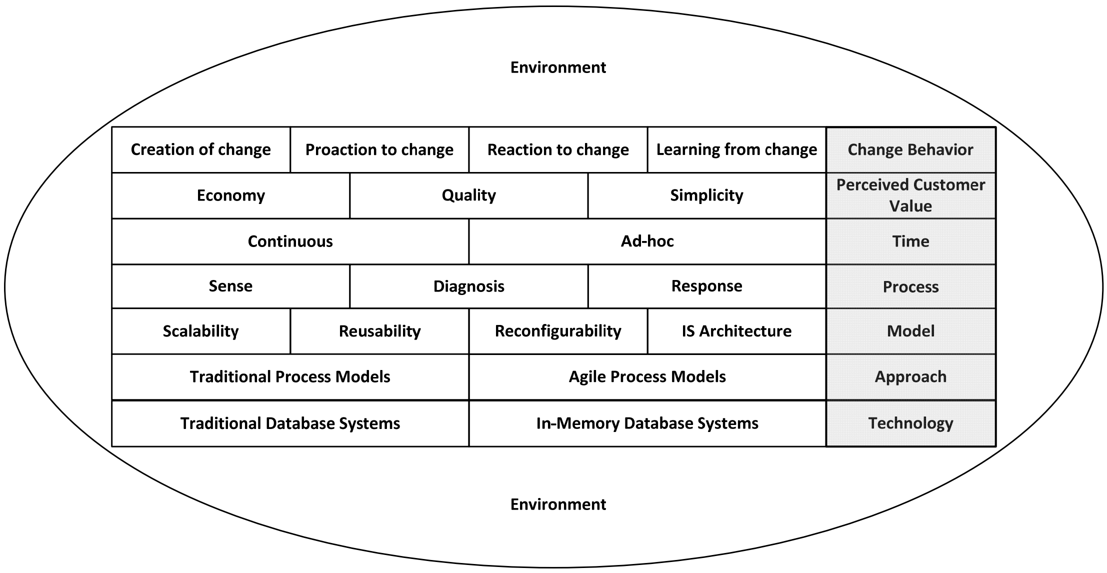

Figure 1. Framework for BI agility

Knabke and Olbrich (2013) identified the BI creation process, i.e. approach, as one aspect of BI agility. Unfortunately, the observed organization did only focus on a technology shift and did only use one project approach, which was a traditional one. Therefore, we neglect the dimension approach in our study as we lack data to be analyzed. Nevertheless, to the best of our knowledge, no study analyzes how a technological advancement like IMDB affects BI in terms of agility in a real-life case. Thus, our study attempts to fill this research gap by analyzing how IM-based BI behaves according to the agility dimension above.

3 RESEARCH DESIGN – CASE STUDY RESEACH

3.1 Case Study Research

We decided for case study research to determine how IM technology in particular affect BI agility. According to Yin (1994) a case study is "*an empirical inquiry that investigates a contemporary phenomenon within its real-life context, especially when the boundaries between phenomenon and context are not clearly evident*" (Yin 1994, p. 13). We believe that the method of case study research is well-suited for our problem for several reasons (Dubé and Paré 2003; Yin 1994). First, case study research provides a way to analyze the impact of technology on BI agility in a natural setting of a real-life use case without exerting control over the process or setup of the BI transformation project using IM technology. Second, since the BI agility phenomenon we are investigating cannot be separated from the BI transformation project, the boundaries between phenomenon and context are not clearly obvious. Third, we use multiple source of evidence, namely qualitative and quantitative data.

Our case study research method consists of three steps (Dubé and Paré 2003). The first step is research design. It refers to the "*attributes associated with the design of the study*" (Dubé and Paré 2003, p. 605). Data collection as the second step describes the quality of the data collection process including the data collection methods (qualitative and quantitative). The third step, data analysis, is concerned with the process description, the use of techniques as well as modes of data analysis.

3.2 Case Study Design: The Quest for Agile BI at a German Sportswear Label

The case study was conducted at a globally acting sportswear designer and manufacturer with several billion € in revenue and a profit of several 100 million €. The company with headquarter based in Germany employed more than 50,000 people in 2014 and is one of the biggest sportswear designers and manufacturers in the world. Its industry has seen some rapid change and fierce competition in recent years. Hence, the company wants to react to market changes earlier than its competitors and introduce agile analytics. In a global BI transformation project the organization aimed to consolidate and transform all global BI applications from different DRDB landscapes into one single, IMDB-based platform. The initiative that started at the end of 2012 and yields to offer high performance reporting and business analytics capabilities based on a consolidated and harmonized data basis with a globally agreed understanding of data structures and key figures ("one version of the truth"). The BI transformation has a high profile within the organization as BI is seen as a main driver to turn data into business relevant information. The initiative sets the foundation for several advanced business scenarios to allow even more fact-based decision making. Examples of these advantages are big data analytics, predictive analytics or integrated business planning which were technically not feasible without the transformation program. The program is planned to be finalized completely in 2015. Nevertheless, some major BI applications have been set live what justifies an in-depth scientific analysis at this time.

The former BI landscape consisted of two major DWH-based BI systems. One DWH system contained all retail-related data. All other BI-related information (manufacturing, finance etc.) was stored in a second DWH system. Both systems are based on DRDB with a necessary performance add-in to meet at least minimum performance requirements. According to the BI responsible no reporting and querying was possible without this additional performance infrastructure (analytical database in

Figure 2). In the new landscape only one DWH-based BI system exists which is completely based on an IMDB. The overall system landscape is shown in Figure 2.

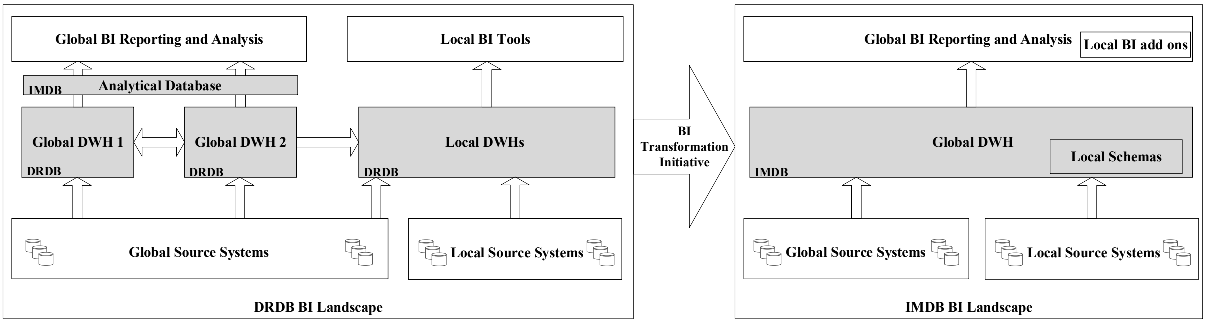

Figure 2. System landscapes overview

3.3 Unit of Analysis

The phenomenon under investigation is the impact of IM technology on the agility of BI. As the organization utilizes a DWH as the basic concept for its BI activities, we use the criteria for DWH constituted by Inmon (1996) as a starting point of our analysis. Inmon claimed that the **integration** of data from (diverse) sources ensures consistency and yields a single point of truth. Second, BI elements should be organized according to the subject areas of the organization (**subject-orientation**). Structures in a DWH need to contain a connection to time to show changes over time (**time-variance**). Fourth, data in the DWH should never be altered (**non-volatility**). Based on the evidence of high BI project failure (Chenoweth et al. 2006; Hwang and Xu 2005; Joshi and Curtis 1999; Olszak 2014; Shin 2003), we assume that the fundamentals of DWH-based BI as operated currently, i.e. based on DRDB, contradict the requirements of today's agile environments. This indicates the importance of agile BI.

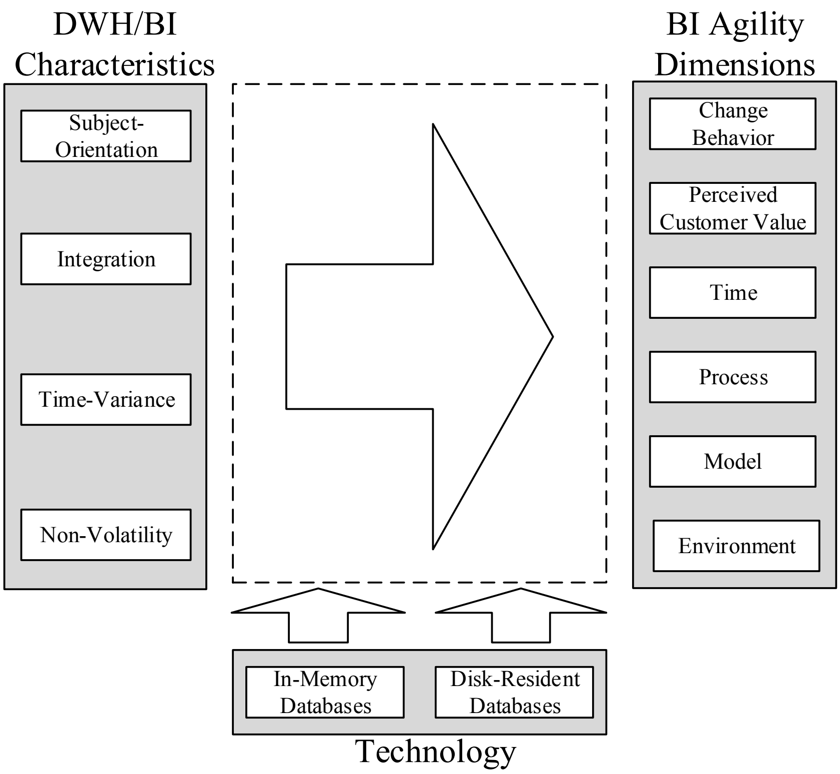

Figure 3. Unit of analysis

To identify the impacts of DWH-based BI on BI agility we propose our research model as depicted in Figure 3. Each DWH-based BI characteristic (Inmon 1996) may influence BI agility (Knabke and Olbrich 2013). As an exemplary impact, integration may affect BI agility in terms of model. As we primary aim to analyze the impact of IM technology on BI agility in our study, the utilized technology is a central construct of our unit of analysis. Therefore, we include technology as moderator in our research model. In a moderator effect the impact of an independent variable (here DWH/BI characteristics) on an outcome variable (here BI agility) depends on a third variable, the moderator variable (here technology) (Hayes and Matthes 2009). Taking the moderator into account, the above stated example can be extended so that the impact of integration on BI Agility in terms of model is influenced by technology.

4 DATA COLLECTION

Different sources of evidence, e.g. qualitative and quantitative data, can be used to investigate the unit of analysis to provide a broad picture of the phenomenon of interest (Dubé and Paré 2003; Yin 1994). Hence, we followed a five-step approach to obtain the necessary data as illustrated in Figure 4. It integrates two data collection techniques as well as qualitative and quantitative data. First, we developed a survey-based questionnaire and scrutinized it with a group of researchers in our institute. The questionnaire was developed following the rules of Dillman (Dillman 1978; Dillman 2000; Dillman 2000; Dillman et al. 2009). The questionnaire contains each question for the new (IMDB) and old (DRDB) BI landscape. Additionally, it includes control questions (Bhattacherjee 2012). Second, we conducted six semi-structured individual expert interviews with six experts at the company of the case study. Within these sessions we verified our research model and the questionnaire. The experts have been chosen from business and IT (three each) to cover both points of view. We selected them as they play a major role in the BI transformation project. The group of experts consisted of project managers as well as responsible functional and technical stakeholders. According to the results of the interviews we adapted our research model and the questionnaire in a third step. Step four contained the conduction of a structured, self-administered survey (Leeuw et al. 2008). The questionnaire was available on the web within a period of three weeks for a closed group invited via email. For each variable, e.g. perceived customer value, the participants rated a set of four to ten statements. The statements "*The old BI systems were easy to understand and use*." and "*The new BI system is easy to understand and use.*" are one example of the dimension perceived customer value. The answers consisted of non-dichotomous 7-point Likert scales. The participants' responses can be aggregated in a standardized manner and used for quantitative analysis with this study approach (Bhattacherjee 2012). We evaluated the answers of the survey using quantitative (statistical) methods (see section 5). We discussed the findings of this analysis with five experts in the last step (one business expert was not available due to holiday season) to find explanations for (especially unforeseen) results (see section 6).

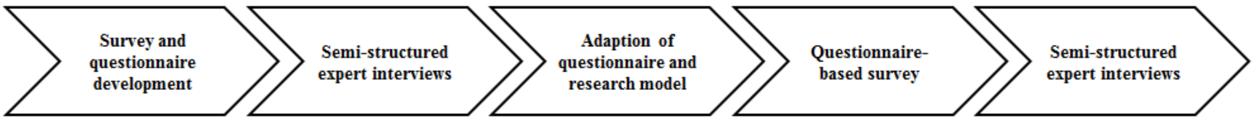

Figure 4. Data collection process

The results of the quantitative evaluation (step four in Figure 4) have been achieved by using a gradual approach that is illustrated in Figure 5. First, we coded the answers of the interviewees to numeric values. The 7-point Likert scale answers from "strongly disagree" to "strongly agree" were coded with "-3" to "+3". Afterwards, we calculated basic survey statistics such as the distribution of IT and business participants. In step three we conducted an analysis of correlation within the BI characteristics proposed by Inmon (1996). Fourth, we analyzed the relation between BI characteristics and BI agility without distinguishing between the used technologies DRDB and IMDB. Last, in pursuit of our second research question, we looked at the impact of BI characteristics on BI agility and how the moderator variable technology affects this relation. For step three we used the standard statistical method of analysis of correlation. For the quantitative analysis of step four and five in Figure 5 we applied partial least squares (PLS) as an established mathematical procedure (Chin 1998; Kline 1998; Rönkkö et al. 2012) to identify the path coefficients (PC). Various approaches exist to test the existence of moderation depending on the scale of the moderator effects (Henseler and Chin 2010). Based on the setting of the use case we used a pragmatic approach to determine the moderator effect of the variable technology. Since the assumed moderator is dichotomous, i.e. only has two values (old BI system, new BI system), a moderating effect can be assessed by a group comparison. Therefore, we calculated the difference between the PCs for the old and new model. This difference can be interpreted as the moderating effect of the variable technology (Henseler and Fassott 2010).

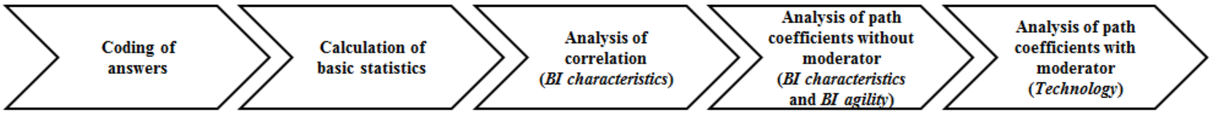

Figure 5. Steps of the quantitative survey evaluation

Both, the BI characteristics as well as the dimensions of agility are not directly measurable and were therefore modelled as latent variables (Backhaus et al. 2013). Thus, we assigned indicators to each latent variable. Statements in the questionnaire represent these indicators. Participants of the survey rate their agreement according to the statements. Each of the latent variables is then determined as a weighted linear combination of its indicators. The dependent latent variables are a weighted linear combination of the independent latent ones (Backhaus et al. 2013). We choose PLS because it can cope with small sample sizes as well as non-normal data and is adequate for exploratory research (Hair et al. 2011). It is advisable to check for outliers to ensure reliable data quality (Weiber and Mühlhaus 2010). Therefore, we used an agglomerative clustering technique called single-linkage or nearest-neighbor respectively (Backhaus 2011). Such algorithms initially treat every data set as a cluster and then start reducing the number of clusters by joining them until only one cluster containing all data sets is left. The determination of the outliers was done by using a rule of thumb which has been proven in practice (Backhaus 2011). For the quantitative analysis we used the software tools SPSS Statistics Version 22 (IBM 2013) and SmartPLS Version 3.1.3 (SmartPLS 2014).

5 DATA ANALYSIS AND RESULTS OF THE QUANTITATIVE EVALUATION

The email distribution list contained 187 persons. 69 of the invited persons accessed and started the survey (36.9%). 43 of them completed the questionnaire, i.e. 62.3% of the participants or 23% of all invited persons. By checking the outliers as mentioned above 39 participants remained (20.9% of the invitees). As every participant was asked questions regarding the old and new landscape we achieved a total of 78 answer sets. 14 of the 39 participants (35.9%) have been users from functional or business departments, 24 (61.5%) were from IT and one (2.6%) answered “other”. Regarding their involvement in the BI transformation, three participants (7.7%) were business project members. 13 were IT project members from the organization itself (33.3%) and another 11 were external project members (28.2%) . 12 participants (30.8%) were end-users with no project involvement.

We analyzed the answer sets (n=78) without differentiating between the underlying technologies (IMDB and DRDB) to determine correlations within the DWH characteristics proposed by Inmon (1996). All four variables, i.e. subject-orientation, integration, time-variance and non-volatility, correlate positively and no negative correlations exist. The coefficients are between 0.38 and 0.60. Values below 0.9 are deemed acceptable as very high correlation would question the definition of the latent variables (Huber 2007).

5.1 Dependencies between BI Characteristics and Agility

Table 1 (n=78) summarizes the dependencies between DWH/BI characteristics and BI agility without moderator distinction. Considering four variables within DHW-based BI characteristics and six variables in BI agility, this sub model contains 24 relations. The table shows the PCs between DWH/BI characteristics and the agility of BI. PCs are the weights of the paths obtained by regressions. Every PC should at least have an absolute value of 0.1 (Huber 2007). Four of the 24 PCs did not meet this threshold. In return, 83.3% fulfill the criterion. We applied bootstrapping to assess the significance of the paths. At a significance level of 10%, the resulting t-values (t) should exceed 1.65 (Huber 2007). As shown in Table 1, 41.7% (10 of 24) of the relations are significant at a 0.1 level and meet the criterion.

	Change Behavior		PCV		Time		Process		Model		Environ-ment	
	PC	t	PC	t	PC	t	PC	t	PC	t	PC	t
Subject-Orientation	.02	0.08	.33*	1.90**	.29*	1.89**	.00	0.05	.13*	0.07	.12*	0.83
Integration	.11*	0.81	.17*	1.13	.06	0.50	.19*	1.86**	.10*	0.53	.16*	1.09
Time-Variance	.14*	0.65	.08*	0.46	.05	0.36	.32*	2.45**	.24*	1.27	.36*	2.22**
Non-Volatility	.47*	2.75**	.29*	1.68**	.33*	2.48**	.40*	2.96**	.33*	2.08**	.10*	0.61
Notes: * Path coefficient above threshold (0.10) ** Significant t-value, i.e. t-value above threshold (1.65)												

Table 1. Path coefficients between DWH-based BI characteristics and BI agility

5.2 Impacts of Technology on the Agility of BI

We split the data set (n=78) along the lines of the variable technology as the moderator is dichotomous. This results in two groups of n=39 responses each (DRDB and IMDB) and facilitates the assessment of a moderating effect. Table 2 illustrates the PCs of the PLS procedure for these separate estimates. The impact of the moderator of the variable technology is the difference (Diff) between the new (IMDB) and new (DRDB) landscape (Henseler and Fassott 2010). Although all paths with an absolute coefficient of 0.10 or higher can already be included in moderating considerations (Huber 2007), we chose a cut-off value 0.25 to reflect our more conservative approach.

		Change Behavior	Perceived Customer Value	Time	Process	Model	Environ-ment
Subject-Orientation	DRDB	-0.25	0.14	0.15	-0.22	0.05	-0.03
	IMDB	0.07	0.43	0.47	0.08	0.40	0.31
	Diff	0.31*+	0.29*	0.33*+	0.31*+	0.35*	0.35*+
Integration	DRDB	0.31	0.04	-0.07	0.25	0.01	0.21
	IMDB	0.24	0.39	0.01	0.23	-0.10	0.24
	Diff	-0.07	0.35*	0.08	-0.02	-0.11	0.03
Time-Variance	DRDB	0.25	0.20	0.07	0.36	0.21	0.41
	IMDB	-0.10	0.20	0.07	0.23	0.40	0.22
	Diff	-0.35**	0.00	0.00	-0.13	0.19	-0.19
Non-Volatility	DRDB	0.44	0.38	0.43	0.57	0.45	0.17
	IMDB	0.58	-0.02	0.27	0.45	0.23	-0.03
	Diff	0.14	-0.41**+	-0.16	-0.12	-0.22	-0.20
Notes: * significant positive moderating effect (difference >= +0.25) ** significant negative moderating effect (difference <= -0.25) + Deviation in Diff due to rounding							

Table 2. Comparison of path coefficients as a moderator analysis

In total, nine moderated paths were identified (37.5%). In seven cases (29.2%) the BI transformation appears to enhance the relationship between DWH-based BI characteristics and agility. In contrast, in two cases (8.3%) the relationship seems to have deteriorated. The results have been analyzed in a second round of expert interviews and are described in section 6.

5.3 Technical Considerations

In addition to the quantitative evaluation of the survey data we conducted a technical analysis of the BI transformation. The former BI landscape consisted of two BI systems, whereas the new IMDB-based BI system is implemented in one system (see Figure 2).The transformation project reduced in the number of objects and hardware used. For the old DRDB systems 32 servers were needed whereas the new system requires 12 servers. The database size dropped from 39.5 terabytes (TB) to 4.6 TB (-88.2%). The number of objects used for reporting and data analytics including the underlying architecture was reduced from 35,153 to 5,517 or -84.5%. But, one has to keep in mind that the BI transformation project is not completely finalized yet. Thus, the storage space consumed as well as the number of objects will possibly rise, but be less than before. Performance as well as flexibility increase of the BI application played a major role at the organization when deciding to implement the transformation program. This was not only done by migrating BI application and its data to an IM-based technology. Moreover, the program consolidated data models and adapted business logic within the applications. This complicates the process selection for a performance analysis to be able to get reliable and comparable results. The process recommended as comparable by the organization is a sales and margin reporting. This application enables users to do general analysis on sales and margin figures, e.g. from gross sales down to standard margin by customer, article, reporting unit, period and further dimensions.

The information logistics process at the studied organization consists of several layers as illustrated in Figure 2 and is typical for DWH-based BI. First, data is extracted from the source systems to the extraction layer. Second, the data is cleansed, consolidated and harmonized and afterwards enriched with application or functional specific logic (corporate and propagation layer). If a DWH is based on DRDB, usually a reporting layer for performance reasons is required (data mart layer). For the performance view on this technical consideration we analyzed the end-to-end process of sales and margin reporting from data extraction from the source systems until the data is available for analysis. Overall, the process to provide data for reporting and analysis decreased from 01:51 hours to 9 minutes (-92%) for a comparable data set (~0.2 million records). The DRDB system required a data mart layer and additional technical infrastructure for performance reasons. This layer is not necessary in the new landscape (-100%).

Process Step / Data Flow	DRDB BI systems (hh:mm:ss)	IMDB BI system (hh:mm:ss)	Difference
Data Mart Layer	01:41:31	00:00:00	-100%
Corporate and Propagation Layer	00:08:05	00:08:36	+6%
Acquisition Layer	00:01:44	00:00:40	-62%
Overall	01:51:19	00:09:17	-92%

Table 3. Exemplary ETL-process comparison between the old BI and new BI landscape

6 IMPLICATIONS AND REFLECTION IN SEMI-STRUCTURED EXPERT INTERVIEWS

6.1 Interpretation

Referring to our first research question we identified Inmon's criteria to be complementary factors. They correlate positively and do not contradict themselves. Hence, following all of Inmon's criteria does not result in any disadvantageous effects for the DWH approach in practice. Regarding the conflict of agility requirements with the common DWH-based BI approach it seems to depend on the underlying variables and the underlying technology. All PCs are positive with ten of 24 significant when looking at the complete answer set (Table 1). This would object our first research question. But, the first impression changes if the DRDB and IMDB landscape are considered separately. For the DRDB landscape four negative relations exist, with two PCs below -0.1. For the IMDB-based BI system also four negative PCs exist, but with all of them between -0.1 and -0.02. Although this is only a weak indication, it seems that the basic DWH assumptions have a stronger negative impact on BI agility if based on DRDB.

IMDB technology has a significant positive impact on nearly a third of the relations (seven out of 24 or 29.2%) between the basic DWH assumptions and the agility of BI according to Table 2. It has a positive moderating effect on the influence of subject-orientation on every agility dimension of BI. The differences in PCs were significantly positive for all of the six paths. The development of the new BI system was driven by key business players that enabled the IT department to ensure as many business benefits as possible. The IM technology enables the implementation of metrics and KPIs that were not realizable before due to performance limitations. The experts mentioned the simplicity and reduced time to achieve changes in the IMDB-based BI system as one of the main achievements of the BI transformation. Another new feature are drill maps which support the end-user to better analyze the data and find root causes for changes in important KPIs. The underlying IMDB technology allows for on-the-fly calculations and thereby increases customer value and business benefits. In addition, the experts agreed with the participants' opinion that the new BI system allows for a higher level of self-service. They asserted that this is a combination of the system consolidation, the computing power of the IMDB and the choice of the frontend-tool. A non-technology related reason might be the fact that people are still learning how to exploit all the possibilities of ad-hoc reporting. Overall, the interviewed experts mentioned that the transformation has in fact materialized in a boost of agility.

The effect of integration on perceived customer value also has improved remarkably by using IM technology. Besides the positive influence of the new technology itself, some experts highlighted the effect of the system consolidation into one database as there is now a single point of truth since all information is now combined at one place and consistent. This simplifies the creation of reports which span across some of the formerly separated data and might therefore even drive changes in the reporting culture. The BI personnel finds itself having formerly unknown possibilities in reporting by merging data. This creation of functional spanning reports in the DRDB systems could only be achieved by time- and effort-consuming transformations which in itself lead to redundancies. Moreover, the IMDB-based BI enables the storing of local master data which contributes to both, the level of self-service and the possibility of ad-hoc changes since there is no need for global agreement before a change in local master data can be decided.

In two of 24 cases the impact of IMDB is negative (8.3%). Time-variance negatively influences the change behavior of the BI system. One explanation of the experts for the negative effect was that the number of snapshots were reduced in the new BI landscape. This limits the possibility of getting more insights into business backgrounds such as backtracking delivery statuses and its reasons for backlogs. Summarizing, the negative effect was not caused by the IM technology itself but by decisions to reduce the scope of the BI system.

The BI transformation had negative consequences for the effect of non-volatility on the perceived customer value. Although non-volatility seems to support the perceived customer value in the old BI landscape, this effect disappeared when moving on to the new BI landscape. Confronted with this fact, the reactions of the experts were again mixed. One expert stated that the current state of the data might temporarily be more volatile. Another reason that both the IT and the business expert from one department gave is related to the explanation for the negative impact of time-variance and change behavior. Snapshots have been reduced from a daily to a weekly basis. This drastically limits the ability to track and analyze fulfillment rates of deliveries to customers over time, which is an important KPI in the organization of the use case. Again, the negative impact is more related to a business decision after weighing the necessity of daily snapshots against storage expenses than to the capability of technology to moderate BI agility.

6.2 Evaluation of the Methodical Problems in the Study of a Single Case

Lee (1989) identified four problems that are relevant for case study research in management information systems. In particular, he highlighted the challenges for case study research of a single case in a natural, real-world setting. These are the problems of **making controlled observations**, **making controlled deductions**, **allowing for replicability** as well as **allowing for generalizability**.

We evaluated a single running artifact in our case study. As one part of our analysis we used quantitative analysis by means of statistics. As natural in MIS case study research we do not have controls as found in laboratory experiments. But, we used statistical controls (e.g. control variables) to achieve controlled observations. Second, the evaluation of our questionnaire used quantitative statistics. As these are using mathematics as subset of formal logic, we achieved the second claim of Lee which is making controlled deductions. Third, the postulation for replicability is hard to achieve for MIS case studies in a real-world setting as it is very unlikely to observe the same setting of individuals, groups, social structure, hardware or software again in the same way (Lee 1989). But, the same theories could be applied to a different set of initial conditions. Although observations are hardly replicable in MIS case studies, its findings are replicable (Lee 1989). Our presented case study is based on the BI transformation of two DRDB-based BI landscapes into one system based on an IMDB. A DWH builds the basis for BI in both environments. These settings are not limited to the considered organization but can be repeated at other companies with a different set of initial conditions. The theory assumption that IMDB enables BI agility can be transferred to different organizations, too. As the focus lies on IMDB and DWH, the existence of a two to one system transformation can even be neglected. Thus, the case study's findings, i.e. proofing or disproving our theory, are replicable. Last, the major design assumption in our case study is the existence of a DWH-based BI system which is transformed to an IMDB. The company of the case study was a large-size sports fashion company based in Germany. Yet, the architecture of the BI system using a several layer approach is typical for DWH-based BI, regardless of size, branch or culture of the organization. That being said, organizational processes and culture of decision making certainly may impact design decisions. Nevertheless, our theory is generalizable if it is confirmed by additional case studies in a variety of situations. Thus, we are convinced that we made controlled observations and deductions in our study that analyzes a single running artifact and the core results are replicable and can be generalized.

6.3 Limitations of the Study

The results must be carefully reflected in the light of the study's limitations. The weaknesses of the model as explored in the evaluations might well be attributed to the relatively small sample size (n=39 and thus 78 answer sets in total). The results of a bigger survey among people from different industries might differ from the ones presented above. Obviously, a higher number of participants and resulting data sets would have been desirable and might have stabilized the results, but lamentably could not be realized due to the limited number of potential participants. However, this case study serves as a starting point as the intensive usage of IMDB as technology basis for BI is just beginning in an organizational context. Companies are just starting to explore the full capacity and we assume that positive impacts will even rise in the future. The negative moderating effects in our case study are only partially connected to the introduction of the in-memory technology as confirmed by the experts during the interviews. Limitations for end-users are not necessarily a consequence of the technology, but rather a compromise which was made as a management decision for monetary reasons. Regarding the performance and technical investigation we need to point out that the BI transformation is not finalized in terms of migrating applications to the new landscape. This may have an impact of the utilized hardware. But, continuous improvements is an often found phenomenon in IS and referred to as design cycles in design science. Comparing end-to-end process is hardly possible in every detail. Nevertheless, our examination delivers an insight into the order of magnitude that IMDB offers in terms of performance gains. The type of study may also be limiting: An observational study like this is not able to control confounding variables like the usage of agile process methods and could bias the findings.

7 CONTRIBUTION AND OUTLOOK

Our overall research goal is to contribute to the field of agility in the context of BI. We consider this discussion as highly valuable, since we assumed that the underlying requirements of DWH and thus BI (Inmon 1996) contradict the agility framework introduced above and hence, the agility of BI in general. Therefore, we evaluated our design assumptions on how agility in decision support systems can be achieved through a case study analysis of a German globally operating sportswear label. Though limited to observations in a single case study, the results indicate that some criteria for building DWHs as well as the agility criteria seem to be complementary and positively correlated. But above all, our analysis showed that IM technology appears to be a technology enabler for agile BI. Referring to our second research question, some DWH-based BI characteristics get positive effects on BI agility if IM technology is used or the impact is only positive when using IM. Moreover, practitioners and other organizations will benefit first-hand from these concepts. For instance, subject-orientation positively influenced all BI agility dimensions by using IM technology. IMDB enables the realization of KPIs that could not be implemented with former technologies. In addition, IM technology achieves simplicity and reduced time and effort for change requests at our case study organization. This will move decision support by BI systems away from solely dispositive, analytical support with historic reflections to actively steer the future using data already available in companies. Besides the positive integration effect of the system consolidation, BI customers can now conduct functional spinning analysis. Moreover, IMDB-based BI contributes to a higher level of self-service and ad-hoc analysis. The gain in perceived customer value will affect the way BI supports the enterprise organizations' decision process as well as the corporate strategies, resulting in contribution to corporate success.

In our prospective research agenda we will pick up on the limitations of the study. Next, experts (scientists and practitioners) at The Data Warehouse Institute (TDWI) will be surveyed. This ensures industry-spanning responses from BI practitioners, consultants as well as scientists to validate our results. It will also mitigate ambiguous statistical results due to targeting a heterogeneous group or a bigger sample size. Our future research will also extend the research by including the analysis of approach (e.g. agile process methods) as potential moderator to achieve BI agility.

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