The Impact of In-Memory Technology on the Agility of Data Warehouse-based Business Intelligence Systems - a preliminary Study among Experts

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Abstract. A vital aspect for organizations' competitiveness in dynamic market conditions is to draw faster conclusions out of changing circumstances. The Information system itself must become more adaptable to better support corporate strategies. This is particularly challenging in the domain of Business Intelligence (BI) since the underlying architecture of decision support systems is not built upon agility, but on reliability and robustness. This paper investigates whether the characteristics of Data Warehouse-based BI impact the agility of BI. The focus is to identify if/how technological trends like in-memory (IM) databases can achieve more agility in BI. This paper explains the background research, proposes a hypotheses model, describes the research approach and shows the results of a survey among BI experts. The findings indicate that IM may act as a technology enabler for agile BI. If IM technology is used, the impact of some DWH/BI characteristics on BI agility is significantly positively influenced.

Keywords: Business Intelligence, Data Warehouse, Agility, In-Memory Database.

1 Introduction and Motivation

Organizations are faced with frequently changing market developments that result from underlying trends such as an increasing global integration or financial and political uncertainties. In order to provide sustainable success in such environments, managers must be able to adjust their strategies and execution within an adequate time frame [1, 2]. Information Systems (IS) need to be aligned with a company's business strategy to optimally support these tasks. The amount of data to be incorporated in management decisions has amplified during the last years and the importance and potential of data-related problem solving has grown [3, 4]. Therefore, quick adaption of IS is crucial to sustain competitiveness of a firm [5, 6]. Business Intelligence (BI) as a distinct class of dispositive IS offers operational and analytical functions for the entire organization and is based on a reliable and consolidated data basis to support these decisions. But, requirements like including new data sources or enhance existing

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analysis to other departments frequently change in turbulent environments. Thus, achieving agility is challenging [7, 8], especially because existing IS and BI applications in particular have reached a certain level of maturity. 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 [9]. We assume that a firm will accomplish sustained competitive advantage if it is able to apply agile analytical capabilities. We further believe that analytical capabilities supported by BI positively influence corporate success in return. Moreover, there is evidence that they support long-time competitiveness – especially in quickly changing environments [10].

A BI system is usually built on a Data Warehouse (DWH). Hence, the question remains how such a (by design rather static) BI system can behave more agile. A discussion about agile process or management methods like Scrum [11], Extreme Programming (XP) [12]) or BI-adapted versions [13, 14] are not in the center of our research. These principles deliver without a doubt high value in theory and praxis, but concentrate on the process how a BI system is created. Instead, we plan to investigate how a DWH and thus BI itself can become more adaptable. This may be achieved by different architectural approaches [15], adequate organizational structures and processes [16] or technological support such as in-memory (IM) storage concepts [17]. Current research activities identified significant reductions in the time required for information retrieval when applying in-memory databases (IMDB) [18]. Besides performance aspects, the usage of IMDB can reduce the number of layers required in a DWH [19]. Furthermore, IM based column storage obviates pre-computation and pre-aggregation of data and promises to be well-suited for BI [18]. Until today, the impact of IMDB on the agility of BI has not been sufficiently investigated and mostly promoted by software vendors. Therefore, the aim of this paper is to investigate if and how the usage of IMDB affects the adaptability of BI. To achieve this goal, we conduct a quantitative study using a questionnaire based survey to address the following research questions:

- How do the requirements of BI agility relate to the common BI approach and its underlying DWH concept?
- Do in-memory based technologies positively affect the agility of the BI?

To get a common theoretical background, we build upon current BI literature and the value of agility to derive our research model. Next, we present the early results of our pre-study and provide a first interpretation. In the last section, we give more insights in our ongoing research by addressing the studies limitations and drafting an outlook to future research opportunities including their possible implications.

2 Background

2.1 The dispositive Behavior of Business Intelligence Systems

BI systems are a broad category of IS that support decision makers through business analyses on the basis of internal and external data [20, 21]. They summarize a set of technologies, applications and processes for gathering, storing, accessing and analyzing data that helps users make better decisions [22]. Thus, they have been introduced to measure corporate performance based on IS data as well as to support problem and opportunity identification, decision-making and alignment of operations with the corporate strategy [23]. Most multidimensional BI systems utilize the DWH approach [21, 24] as a conceptual basis in order to systematically extract, harmonize and provide data. A DWH is built to fulfill fundamental requirements [9], i.e. integration, subject-orientation, time-variance and non-volatility.

BI systems offer enormous potential to contribute to corporate success. Recently, a worldwide survey of more than 2000 CIOs identified BI as the number one technology priority [25]. Therefore, many organizations have launched BI initiatives with the intention to implement or improve these systems [26]. There is evidence, however, that a significant number of organizations have failed to realize the expected benefits of BI [27, 28]. Yet, BI implementation projects are expensive, time-consuming and risky undertakings [29, 30].

2.2 The Value of BI Agility

The idea of agility in organizational and business contexts has been established in practice and discussed in literature for decades. It originated from the field of manufacturing [31, 32] and has also been used for several years in different management areas. Nevertheless, the definition of agility is ambivalent in scientific literature and industry [31, 33]. Researchers have provided a wide range of definitions (cf. appendix in 32) - often with deficiencies in the academic approach to arrive at these definitions [32]. In contrast, Conboy and Fitzgerald [34] conducted a cross-discipline literature review to derive a holistic definition of agility. They investigated the underlying concepts of agility, i.e. flexibility and leanness [35, 36]. In particular, 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" [37]. This definition is in line with the definition of Pankaj et al. [32]. They 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 an adequate time frame. In short, it seems that the underlying assumptions of BI with underlying DWH concept which aims toward robustness and reliability contradict the requirements of today's agile environments. Since IS are aligned to the corporate strategy of an organization neither the strategic value of IS agility nor the potential of BI is arguable. But, how can both be fulfilled to ensure organizations' competitiveness. Our assumption is that BI can contribute to IS agility and thus corporate success as a firm's strategy.

3 Research Model

Many organizations use the concept of a DWH as basis for BI. Hence, a DWH can be treated as a major attribute of such BI systems. Our assumption is that the characteristics of DWH influence BI in terms of agility. Currently many organizations plan to invest in IM technology. This is often related with changing the underlying database from disk-resident database (DRDB) to IMDB. Therefore, we only focus on this technology and no other advancements like cloud computing, etc. Thus, we applied the framing of BI agility (see) as described by Knabke and Olbrich [38]. In a structured literature review they analyzed the individual components of the agility definitions in an IS context in general and a BI context in particular. As a result, similar constructs of agility were grouped. These BI agility dimensions are change behavior, perceived customer value, time, process, model, approach, technology and environment.

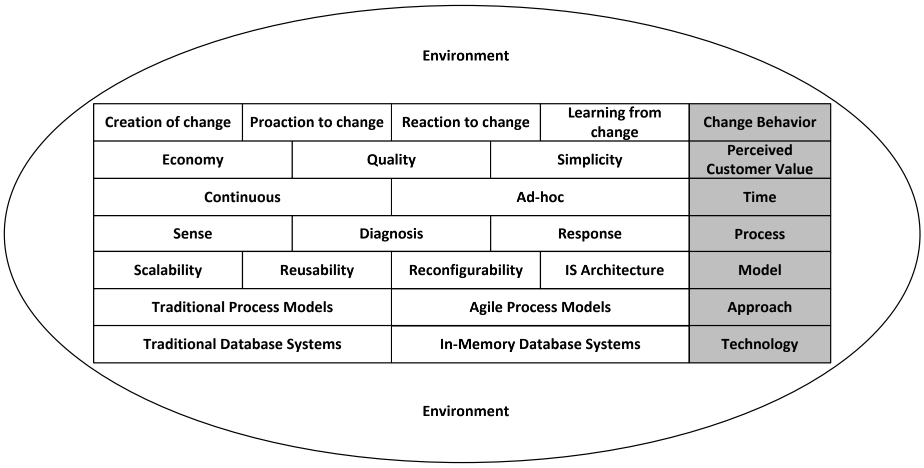

Fig. 1. Framework for understanding BI agility

The aim of our research is to identify the significant relations between basic characteristics of DWH/BI (independent variable) as described by Inmon [9] and their impact on BI agility (depending variable) as depicted in Fig. 2. The figure shows the baseline model within the dotted rectangle in the research model in Fig. 2. One exemplary hypothesis is. *Hypothesis x: Integration affects BI agility in terms of model.* In our opinion the DWH approach does not influence technology. Instead, we assume that new technologies like IMDB positively support the criteria for DWH constituted by Inmon [9]. In addition, the utilized technology (IMDB vs. DRDB, i.e. disk-resident databases used in conventional BI landscapes) is crucial while implementing BI systems. Therefore, the influence of technology is included as central construct of our research model and designed as moderator variable. In a moderator effect of an independent variable (here: DWH/BI characteristics) on an outcome variable (here: BI agility dimensions) the size or direction depends on a third variable, the moderator variable (here: technology) [39]. By taking the moderator into account, *Hypothesis x* would be extended to *Hypothesis xt*: *The impact of integration on BI agility in terms of Model is influenced by IMDB.* For instance, using DRDBs requires some layers in most organizations for performance reasons. IMDBs supersede these layers. Hence, IMDB would impact the architecture of the data model positively in this case as it eases the effort to achieve the single source of truth of the organization’ source systems within the DWH. As the approach, i.e. traditional vs. agile process model is not the focus of this paper it is neglected in the current research model.

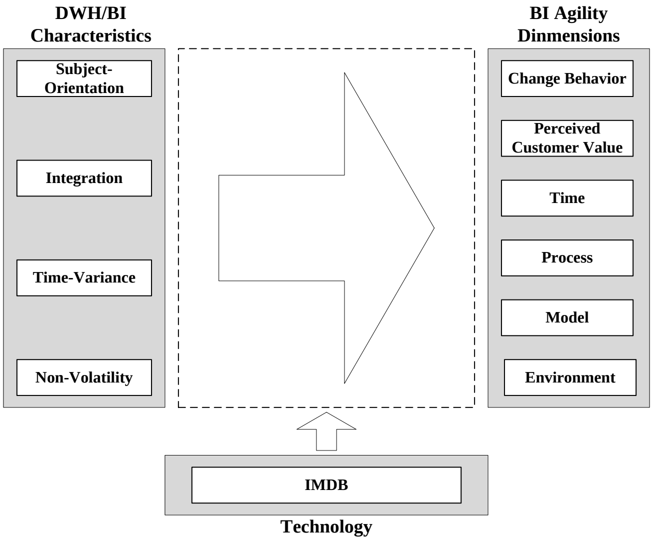

Fig. 2. BI Agility Research Model

We reach 48 potential hypotheses including the moderator. 24 (4x6) hypotheses describe the correlation between the independent variables (DWH/BI characteristics) and the dependent variables (BI agility dimensions). Another 24 (4x6) arise by including IM technology as moderator. There are multiple ways to lower the number of hypotheses in order to conduct in-depth analysis. One alternative is to start with a qualitative study, e.g. with expert interviews and only investigate the relationships identified by the experts in more detail. But, this could exclude relevant hypotheses based on the biased opinion of a few. Thus, we chose a different, more explorative approach as a starting point. This quantitative approach uses statistics to first identify correlations between DWH/BI characteristics and BI agility before analyzing the reason/background of this relation. One appropriate and acknowledged method for causal relations in the field of IS is a structural equation model [40] as depicted in Fig. **2**. The relationships within DWH/BI characteristics themselves and between DWH/BI characteristics and BI agility are analyzed with analysis of correlation. In order to learn more about the influence of IM technology, potential causes of BI agility through DWH/BI characteristics are identified using ordinary least squares (OLS) regressions in a moderator analysis [39]. The suggested approach has several advantages. First, it will eliminate irrelevant hypotheses in an objective manner by using correlation analysis. At the current stage of our research agenda a qualitative study may even restrict objectivity and validity of results. Moreover, this approach will show positive and negative impacts of these hypotheses. Our assumption is that IM technology positively affects the agility of BI in comparison to traditional stored database management systems like DRDB. We assume that this holds true for all criteria of agility or at least that no negative impacts exist.

We executed a pre-study with the data collection technique of a structured, self-administered survey [41] to verify our approach. The questionnaire, which was developed by the authors, was available on the web for a pre-selected group of BI experts. The group was selected among a specialized BI consultancy. The survey was accessible for the group of more than 220 BI experts from Germany and Switzerland for a period of three weeks. This approach is better suited to analyze a wide variety of BI systems behavior compared to field experiments or separate expert interviews and to achieve bigger sample sizes. Field experiments or expert interviews can only focus on their actual systems and would narrow the size of the study. In addition, a survey based approach allows to aggregate the participants' responses in a standardized manner and use it for quantitative analysis [42]. The questionnaire was developed following the rules of Dillman [43, 44]. Before making it available online, a group of researchers in our institute have scrutinized our questionnaire to ensure high quality and quantity of questions and responses. The reworked questionnaire focuses on each component of the research model separately. (i.e. dependent, independent and moderating variable). Each attribute like subject-orientation in DWH/BI characteristics (independent variables), model in BI agility dimensions (dependent variables) as well as IMDB in technology (moderator) consists of 2 to 5 statements. One of these statements for subject-orientation is "*Data in the data warehouse is linked according to functional topics or subject areas*", whereas *"New data sources can be easily incorporated into the BI systems"* is an example for a statement of model and *"The BI systems are based on in-memory technology in all areas/layers (end-to-end data flow)"* one of technology. The answers consist of non-dichotomous (7-point Likert scales) or dichotomous (yes/no) rating scales. In addition, the questionnaire includes control questions [42] and asks for personal and organizational background of the participant.

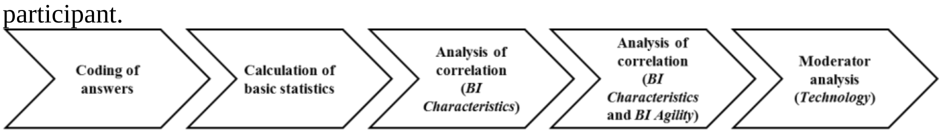

Fig. 3. Gradual Survey Analysis Approach

We achieved the corresponding results by using a gradual approach (see Fig. **3**).They are presented in the remainder of this paper. In the first step, we coded the answers of the interviewees to numeric values. Dichotomous answers "yes" and "no" have been coded as "1" and "2". The 7-point Likert scale answers from "Strongly Disagree" to "Strongly Agree" were coded with "1" to "7". Afterwards, we calculated the mean of each variable (e.g. subject-orientation) within a component of the research model, i.e. DWH/BI characteristic, BI agility, technology. In the third step we conducted an analysis of correlation within the DWH/BI characteristics proposed by Inmon [9]. Fourthly, we analyzed the relation between DWH/BI characteristics and BI agility, again by using analysis of correlation. Last, in pursuit of our research question we looked at the impact of DWH/BI characteristics on BI agility and how the moderator variable technology affects this relation. For steps 2 to 4 we used the standard statistic method of analysis of correlation (Pearson, bivariate). In step 5 we used a moderator analysis based on an OLS approach [39]. For each analysis we used the software tool SPSS Statistics Version 22 [45], including a SPSS software plug-in for the moderator analysis [39] in step 5.

4 Early findings

The email distribution list contained more than 220 addresses. 73 participants accessed and started the survey. 39 of them completed the questionnaire (53%). 26 of the completed surveys were valid in every question, i.e. no blank answers. Considering each attribute of DWH/BI characteristics (subject-orientation, integration, time-variance, non-volatility), BI agility (change behavior, perceived customer value, time, process, model, environment) and the moderator (technology) the answers are close to each other, i.e. values are grouped around the mean (standard deviation below 1.34). Also, the standard error for the observed sample size is relatively small (between 0.12 and 0.26). The margin of error at the 95% confidence level is 1.96 standard errors away from the means. As indicator for the soundness of the model, the margin of error is between 0.24 and 0.51 for the population in our pre-study.

4.1 Correlation within Inmon's DWH/BI Characteristics

Table 1 shows the coefficients of correlation of the DWH/BI characteristics proposed by Inmon (1996) among the answers of the 26 participants with valid answers. Most of the characteristics do not have a significant relation with another one (4 of 6 cases or 67%). Besides that there is no negative correlation – neither significant nor not-significant. The variables within DWH/BI characteristics correlate positive significant in 33% (2 out of 6 cases). In particular, non-volatility and integration show a moderate positive correlation (.418 with significance at the .05 level). The relationship between integration and Time-Variance is strongly positive (.555 and highly significant at the .01 level).

Table 1. Coefficients of Correlation (Pearson, bivariate) of DWH/BI Characteristics (n=26)

	Subject-Orientation	*Integration*	*Time-Variance*	*Non-Volatility*
Subject-Orientation	1.000			
Integration	0.328	1.000		
Time-Variance	0.285	.555**	1.000	
Non-Volatility	0.034	.418*	0.287	1.000

Notes: * correlation is significant at the 0.05 level (two-tailed)
** correlation is significant at the 0.01 level (two-tailed).

4.2 Dependencies between DWH/BI Characteristics and Agility of BI

The correlation matrix in Table 2 summarizes the dependencies between DWH/BI characteristics and BI agility. Considering 4 variables within DWH/BI characteristics and 6 variables in BI agility this sub-model contains 24 relations. Nearly half of them (45.8% or 11 out of 24) have a positive, but not significant relation (neither at the .05 nor .01 level). In 3 out of 24 cases (12.5%) we observe negative impacts, e.g. non-volatility and Time or Process, but again none of them are significant. However, 8 correlations (33.3%) are positive and significant at a .05 level, 2 out of 24 or 8.3% of the correlations are strongly positive and highly significant at a .01 level. In detail, subject-orientation and Process correlate with .710 whereas integration correlates with Model with .495 respectively.

Table 2. Coefficients of correlation of DWH/BI Characteristics and BI Agility (n=26)

	Subject-Orientation	*Integration*	*Time-Variance*	*Non-Volatility*
Change Behavior	.437*	.247	.357*	.199
Perceived Customer Value	.222	.429*	.365*	.039
Time	.437*	.267	.125	-.079
Process	.710**	.359*	.288	-.254
Model	.364*	.495**	.046	.198
Environment	-.076	.055	.163	.440*

Notes: * correlation is significant at the 0.05 level (two-tailed),
** correlation is significant at the 0.01 level (two-tailed).

4.3 The Influence of In-Memory Technology as Moderator

A central aspect of our study is the influence of IM technology as moderator on the impact of DWH/BI characteristics on BI agility. Based on the above results it is of special interest if

- the impact of the independent variable depends on the moderator variable
- the influence of the independent variable on the dependent one gets a positive effect when including the moderator
- the moderator can switch negative correlations to positive ones.

Thus, we analyzed the interaction between the independent variables (DWH/BI characteristics like subject-orientation) and the moderator variable (technology) on the dependent variables (BI agility like change behavior).

Table 3. Effects of DWH/BI Characteristics at Values of the Moderator (n=15)

		Subject-Orientation			*Integration*			*Time-Variance*			*Non-Volatility*		
		ß	p	R^2	ß	p	R^2	ß	p	R^2	ß	p	R^2
Change Behavior	BM	.569	.199	.172	-.125	.725	.077	.363	.205	.161	-.076	.838	.060
	Mean	.279	.240		.083	.738		.416	.275		.214	.401	
	AM	-.010	.980		.291	.427		.469	.447		.503	.230	
Perceived Customer Value	BM	.040	.936	.067	.460	.216	.234	.785	.003**	.595	-.601	.128	.098
	Mean	.038	.890		.380	.150		.567	.068		-.083	.745	
	AM	.035	.941		.301	.417		.349	.464		.435	.302	
Time	BM	1.344	.001**	.802	.015	.974	.364	.404	.235	.479	-.389	.413	.317
	Mean	.760	.001**		.096	.760		.688	.140		-.120	.706	
	AM	.177	.550		.177	.698		.971	.198		.148	.774	
Process	BM	1.285	.005**	.612	-.047	.906	.296	.413	.198	.363	-.550	.248	.128
	Mean	.706	.005**		.355	.220		.925	.044*		-.130	.681	
	AM	.128	.715		.757	.083		1.436	.054		.291	.569	
Model	BM	.272	.545	.605	.011	.978	.493	.040	.875	.688	.212	.669	.243
	Mean	.631	.021*		.419	.152		1.007	.012*		.245	.470	
	AM	.989	.032*		.827	.060		1.974	.004**		.278	.609	
Environment	BM	-1.084	.054	.358	.044	.924	.169	.013	.973	.104	.534	.185	.284
	Mean	-.158	.574		.323	.330		.368	.489		.800	.010**	
	AM	.768	.129		.601	.218		.723	.410		1.066	.026*	

Notes: * significant at the 0.05 level, ** correlation is significant at the 0.01 level.

Table 3 illustrates these interaction effects (ß) using moderator analysis [39]. All variables have been z-transformed before conducting the moderator analysis. With z-transformation the results can be interpreted and compared easier. Additionally, two variables with different scales would distort the interaction effect during its calculation. This is omitted by using z-values (z-scores). R^2 is the coefficient of determination and describes the soundness of fit of the model. The analyses in the sections above include all valid responses (n=26) from the survey regardless if the person uses in-memory technology personally or IM is used in their (client's) organization (IM background). But, if we want to investigate the impact of IMDB in detail, we need to restrict our statistics to IM users to get reliable results. Only respondents with hands-on experience in the application of in-memory technology can judge the influence of technology on a solid, non-hypothetical basis. These persons actively use IM technology or work in/for organizations that use IM. Thus, the respondent set has been restricted to these users (n=15 participants).

The applied approach allows for a moderator analysis depending on the value of the moderator variable. Besides looking at the mean usage of IM it is possible to consider "below mean" (BM, one standard deviation below average) and "above mean" (AM, one standard deviation above average) separately. DWH/BI characteristics positively affect BI agility in 25% (6 out of 24) of the relations if IM is moderately (mean) used (significant at the .05 or .01 level). If IM technology is used above average, the effect of DWH/BI characteristics on the outcome variables of BI agility is positive significant at the .05 or .01 level in 12.5% (3/24) of all cases. If technology (IM) is applied below average BI agility is positively influenced in 3 relations (12.5%) at the .01 level. Overall, 7/24 (29.2%) variable combinations are influenced significantly without differentiating between AM, mean, BM or combinations of them.

5 Interpretation of the Findings

5.1 Inmon's DWH/BI Characteristics and BI Agility

Referring to our first research question we identified Inmon's DHW (and thus BI) criteria to be complementary factors. They are either independent (67%) or correlate positively (33%) and do not contradict themselves (see Table 1). Hence, following all of Inmon's criteria should not result in any disadvantageous effects for the DWH approach and thus BI in praxis.

Regarding the conflict of agility requirements with the common DWH/BI approach no general statement can be made. The BI support for agility seems to depend on the underlying variables. In 41.7% (10 out of 24) of the cases DWH/BI characteristic variables correlate positive significant with variables on the BI agility side (Table 2). As stated before, a detailed analysis of individual dependencies is scope of future research. Yet, we could identify viable starting points. For instance, the correlation of subject-orientation and process can be explained by a better process support of a DWH if it is built according to the functional subject areas of an organization. An integrated DWH contains all information related to a topic. This better supports the detection, analysis and response to a change. Moreover, BI customers can conduct functional spinning analysis if the underlying DWH is integrated and reflects the organizations' single point of truth. This generates value for the customer and explains the observation "Integration has a strong positive relation with perceived customer value". In return, if BI is integrated over several functional modules this impacts the underlying model of BI – "Integration significantly correlates with model". This has to be carefully reflected in the study's constraints: A correlation of integration and model may be common knowledge and obvious for BI consultants as building integrated BI is one of their major tasks.

5.2 In-memory Databases as potential technology enabler for BI Agility?

As stated in our second research questions we are interested in the effects of IM based technology on the agility of BI. We assume that only those participants may be able to rate the influence of IM technology if they have existing experience. Therefore we restricted the sample size to the participants with IM background (n=15) in the course of our research.

For the differentiated usage of IM no definite conclusion can be drawn yet. As illustrated in Table 3 in 7 of 24 cases (24.2%) the DWH/BI characteristics show significant and/or strong significant impacts on BI agility using IM. Some relations seem to get a positive agility aspect if in-memory is used (time-variance on process or time-variance on model). By using in-memory technology BI architectures can be condensed by reducing layers that were needed for performance reasons only. If the connection of time to characteristics and key figures within a DWH can be implemented with less complexity by using IMDB, a better process support in terms of sensing, diagnosing and responding to change is enabled which explains the positive effect of time-variance on process. The reduced complexity in architecture may also be a reason for the very positive impact of time-variance on model. Time-variance is the fact that characteristics and key figures should have a connection to time and that historic data is kept in a DWH. Historic records and progress needs to be made consistent and transparent which generates large data volumes. By using IM technology data can be stored more efficiently, e.g. in column-based concepts [18], and with reduced architecture complexity [19]. The fact that the effect gets even more positive when using IM above average supports this hypothesis.

Another important aspect is that the effect from subject-orientation on model gets better on a significant level if IM technology is used above average. Again, the reduced complexity of the architecture allows for a well-structured and clearly oriented data model if it is driven by subject-orientation.

With a consistent and persistent DWH (non-volatility) users can derive conclusions in multiple directions on a stable basis - e.g. for business processes or for their own organizations (environment). Handling huge amounts of data in an acceptable timeframe could not or only hardly be achieved for some business processes with former technologies like DRDB. Using in-memory technologies supports these processes or processes can even be newly established which positively impacts the environment of the BI system, e.g. the organization.

Interestingly, some relations (subject-orientation and change behavior, integration and perceived customer value, integration and process, integration and model as well as time-variance and change behavior) have been positive significant without moderator consideration but are not significant anymore when analyzing the detailed usage of IM technology. Such relations will be in the center of our future work.

6 Implications, Limitation and Outlook

Our overall research goal is to contribute to the field of agility in the context of BI based on a DWH. We consider this discussion as valuable since we assumed that the underlying requirements of DWH as a basis for BI [9] contradict the agility dimensions of BI. Such demands for agility in Business Analytics are currently widely discussed and supported by disruptive trends like Big Data [46]. We can only make statements for certain variables given the results of our pre-study among BI experts. Moreover, the results and conclusions only apply for those BI-Systems that implemented an underlying DWH architecture. Yet, the results also indicate that some criteria for building DWH as well as the agility criteria seem to be complementary and positively correlated. Above all, our analysis showed that IM may be a technology enabler for agile BI. Referring to our second research question, some DWH/BI characteristics show a more positive effect on BI agility if IM technology is used. Transferred to practice, this would exceed the usage of BI on IMDB as a dispositive IS. Practitioners will benefit first-hand from these concepts since decision support by BI systems will move away from historic reflections to actively steer the future using real-time data. This will affect the way BI supports the enterprise organizations' decision process as well as the corporate strategies – resulting in contribution to corporate success. The results and implications, still of preliminary nature, must be carefully reflected in the light of the study's limitations. Although we presented a few interesting results, the number of responses has to be kept in mind. The results of a bigger survey among people from different industries and especially end users may differ from the ones presented above due to the sample size (n=26 in total and n=15 with IM background). Especially as quantitative statistics are used a bigger sample size is crucial. As BI consultants are specialists in the field of BI some connections between DWH/BI characteristics and agility of BI may be obvious for this particular group. However, as the intensive usage of IMDB as technology basis for BI is just beginning in an organizational context, BI consultants may already be able to rate these impacts. Nevertheless, to generalize and proof the findings of our pre-study, a bigger sample size and industry spanning group needs to be questioned. 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.

In our prospective research agenda we address these topics. In a following step, we plan to survey experts (scientists and practitioners) at The Data Warehouse Institute (TDWI). 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 heterogeneous group or sample size. Based on the results, we will elaborate case studies to find explanations for findings that remain inconclusive at the moment. For example, why does time-variance influence perceived customer value only at a usage of IM below mean or why does none of the DWH/BI characteristics have a significant positive influence on change behavior anymore if IM technologies are used. In the long run, one might ask if IM databases bare the potential to overcome the gap between dispositive and transactional systems altogether.

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