Assessing the Application of the In-Memory Technology - A Comprehensive Framework

Stephan Ulbricht*, Marek Opuszko*, Johannes Ruhland*
*Friedrich Schiller University Jena
Department of Business Informations, Jena, Germany
Email: stephan.ulbricht@uni-jena.de, marek.opuszko@uni-jena.de, johannes.ruhland@uni-jena.de

Abstract*—After a comeback in recent years, In-memory IT systems are among the most promising solutions to solve present and future IT problems. The use of the In-memory technology promises a massive acceleration of query executions, as demanded by the industry in the face of future challenges such as big data and the internet of things. Despite the increased interest in the technology, however, there is a still hesitant spread. One reason is the lack of practical application scenarios that decision makers can apply to their business context. It has been shown that the sole acceleration of the IT-processing is not sufficient for the dissemination in the business environment. The aim of this work is to introduce a framework to support the evaluation of potential In-memory applications. This design science based framework gives practitioners the opportunity to assess the suitability of In-Memory IT-Systems based on their specific demands. The underlying decision factors have been separated based on their characteristics into value-creation dependent and independent attributes. Appropriate methods were evaluated and selected for the collection of the respective significance. The decision model is implemented using the concept of multi-criteria decision making. The framework is applied using 10 potential real-world In-memory use case scenarios. The results show that the presented approach in this work is suitable to both, assess possible use cases and determine cases with high potential.

Keywords–In-Memory IT-Systems; Business Value; Analytic Hierarchy Process (AHP); In-Memory Technology; In-Memory Computing;.

I. Introduction

In this work, we introduce a design science based framework which reflects both, the industrial as well as the scientific claims to identify and evaluate potential In-memory IT-system (IMIS) scenarios [1]. The decision whether to use an IMIS in a company or not is a complex and multi-criteria decision problem. Because of the fundamentally different approach of IMIS, numerous other aspects beside traditional IT requirements have to be considered. This includes aspects such as, relations to employees, customers and suppliers. Furthermore, possible changes in the company's infrastructure [2] has to be evaluated. The representation of this complexity requires a corresponding model which covers all these different aspects. Due to the versatility of the IMIS technology and its potential use in different use cases, the scenarios may strongly differ. Some aspects may be specific and unique, meaning only relevant for a certain scenario. These aspects are directly linked to the creation of business value and are therefore called value-creation dependent. On the other hand, there will be aspects of a scenario that are not directly linked. These are called value-creation independent. According to their specific characteristics the weightings of the value-creation independent factors are determined by the analytic hierarchy processing and the dependent factors are determined by the direct ranking method. The evaluation and interpretation of the framework is presented based on 10 cross-industry use cases.

Enterprises are faced with the challenge of constantly growing data volumes, increasing competition pressure and the permanent need to instantly react to events. This is one of the main reasons why choosing the "right" IT-systems has become a major strategic decision for companies. The selection of the appropriate system may determine the success of a company or in other words, the selection of the wrong system might lead to serious business disadvantages [3]. The challenges and possibilities associated with the term Big Data characterizes today's IT landscapes. In this context, IMIS represent a key technology [4]. Despite promising expectations, the technology has not yet been significantly established in the industry. Companies mainly criticize the lack of reproducible use cases [5][6]. Since the beginning of the boom of the technology, a whole series of application scenarios have been advertised. Based on these examples, which were often tailored to specific sectors and fields of application, many companies could not derive their own benefits and lead in-memory techniques to fruition. According to a study by the consulting company Pierre Audoin Consultants [7], many companies see great potential in the technology, yet there are only a few cases where the benefits are exploited extensively. This is interesting in contrast to the expectations put on the technology to create business value along all steps of the value chain. This accounts for a vertical as well as a horizontal integration. In addition to these open issues in the corporate sector, there is a clear need for a generalizable reference model to analyze and evaluate in-memory scenarios [8][9] from a scientific perspective. Hence, a universal evaluation tool is needed to determine whether IMIS are beneficial or not suited in a specific scenario and vice versa.

The paper is organized as follows. Section II introduces the research background, the existing literature in the field of IMIS and the overall structure of the framework. Section III presents the research methodology including the analytic hierarchy process (AHP) and the direct ranking method (DRM). In Section IV the application of the framework is shown. The final section summarizes the contributions of this work.

II. Research Background

For a better understanding of the evaluation framework it is necessary to gain a deeper understanding of the technical characteristics of IMIS. The idea of using main memory for the storage of data goes back to the 1980's [10] and 1990's [11]. Caused by the high costs and relatively low storage sizes IMIS were basically a niche technology in the past years. With the introduction of the SAP HANA platform [12], the technology experienced some kind of a comeback. Originally, the SAP HANA platform was developed for accelerated and flexible analysis of large data sets. This new generation of IMIS includes a totally different storage concept in comparison to relational databases. The data in In-Memory systems is mainly stored in a column-based manner [13]. The advantage is a better data compression [14]. At the same time a column oriented data storage suits better for analytical tasks [15]. The difference between column and row based data storage is shown in Figure 1.

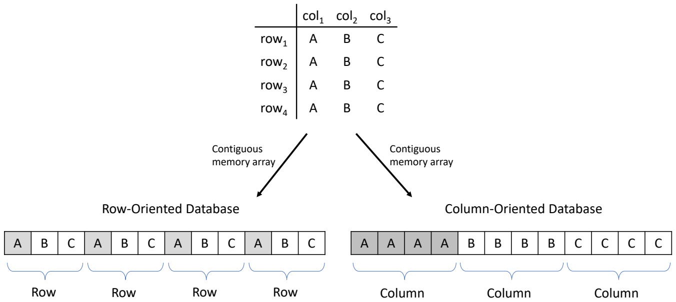

Figure 1. Row- and Column-oriented data layout (adapted according to [15])

In the recent years, the focus on analytical tasks has been extended to hybrid IT-systems. The idea is to store the operational and analytical data entirely in a main memory database [16][17][18]. These hybrid systems are referred to as Online Mixed Workload Processing (OLXP) [19] and Hybrid Transactional/Analytical Processing (HTAP) [20]. Through a common data storage expansive and time consuming extract, transform, load (ETL) processes from the transactional into the analytical system are no longer necessary [15]. As a result, operational data can be used for analysis without major time delays [21].

Due to the different characteristics of analytical and operational tasks, problems and difficulties arise for hybrid systems. The column-based storage of data was originally designed for read-oriented and read-only analysis tasks. A higher proportion of write access typically characterizes operational systems, i.e., enterprise resource planning systems [22], [23]. The merging of these two approaches is often associated with complex join procedures [24][25]. In read-oriented environments, this can reduce the achievable performance improvement promised by IMIS.

A. Problem Context and Related Work

The majority of the early publications in the field of IMIS were characterized by the strong focus on rather technical aspects. To a great proportion, only technical features, such as the column-based storage of data [13], data compression [14] or the persistence of volatile storage media [26] were investigated. The dominance of technical investigations illustrates the strong technologically driven development. Despite its potential, only few studies about the evaluation of IMIS use cases have been published to date. Investigations in the intersection between technology and corporate context have shown that the use of IMIS is not suitable for every application. The speed advantages in comparison to traditional relational databases are related to the number of users and the workload characteristics [27].

The first studies in this field have been carried out by Piller and Hagedorn [8][28][29]. The authors evaluated first case studies in the retail sector. The case studies were evaluated with the aid of various influencing factors. Based on the factors, first application patterns were derived. Another approach to characterize and classify In-memory systems was presented by Winter et al. [30]. They identified stereotypical patterns based on the data volume and the degree of hybrid workload. An alternative approach for the analysis of In-memory applications addresses the business process characteristics of IMIS use cases. Pioneers in this area were vom Brocke et al. [31][32][33]. They developed a value-creation oriented model, which considers first- as well as second-order effects. They conclude that the value-creation is closely related to process change. The evaluation of several IMIS use cases by Bärenfänger et al. [34] confirmed this results. Cunduis et al. [35][36] considered IMIS from a workflow perspective and developed a framework for the value creation. Another approach focuses on the cost benefit effects of IMIS. In this context, Meier et al. developed a model for the economic evaluation of IMIS. Like vom Brocke et al. they distinguish between direct and indirect benefits. Another work following a cost-benefit perspective can be found in [37].

In their publication, [38] Ulbricht et al. introduce a framework combining the findings of the scientific approaches with practical issues from companies and IMIS system vendors. They presented a structured model for the evaluation and analysis of IMIS use cases, taking various factors into account. Despite the different focuses, one thing all approaches have in common. They all consider the characteristics of IMIS use cases from a quite abstract level. The degree of dissemination in individual sectors, however, indicates the different importance of the particular influencing factors. The question arises, why this technology has already been used quite frequently in some sectors and is hardly ever noticed in other areas.

B. Approach

As mentioned before, the evaluation and analysis of IMIS use cases is a complex, multi-criteria decision problem. In order to represent and solve this problem the concept of the multi-criteria decision making (MCDM) is used. This model allows to consider both, the system requirements as well as the corresponding importance. To determine the total utility U, the weighted sum model (1) of the MCDM [39] is applied. In this model, the system requirements are represented as x_i and the significance (importance) as w_i.

$$U = \sum_{i=1}^{n} w_i x_i \quad (1)$$

The creation of the framework follows the concept of the design science research [40]. A fundamental requirement of this approach is the proof of the relevance of the developed artifact [41]. The created artifact in this work is represented as a framework. The overall goal of this framework is the decision support regarding the use of the In-memory technology. The relevance of our investigation can be confirmed both from a scientific and a corporate perspective. In order to meet the scientific requirements, the whole design process is based on proven and context-appropriate methods. The applicability of the artifact is demonstrated by real use cases. The overall approach is summarized in Figure 2.

In order to provide a better complexity handling, we characterize the several influence factors and bring them into a hierarchy in the first step. In the second step, we select suitable methods for the determination of the significance depending on the characteristics of the influence factors. The different

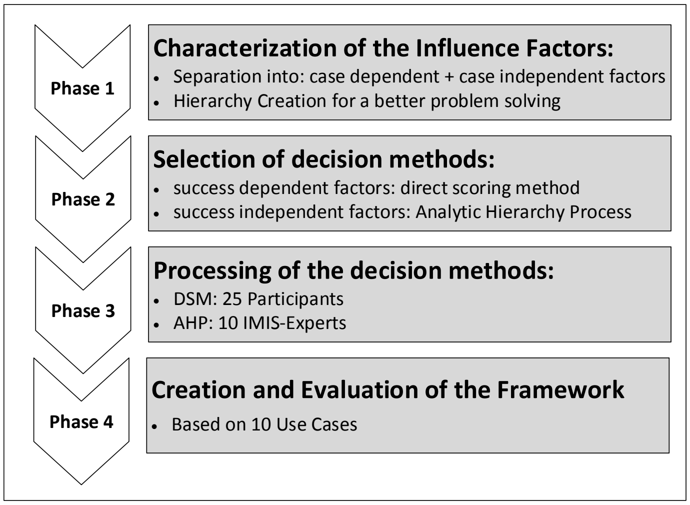

Figure 2. Overview of the Research Methodology

characteristics of the factors lead to a trade off between the operability of the methods and the quality of the results. In the final step, we reveal the results of the utility methods and evaluate the overall framework based on 10 case studies. In this part, we demonstrate the feasibility of our concept by evaluating potential and existing IMIS use cases. Both practical and theoretical aspects are considered in the presented approach. The several steps of the design process are presented in the following sections.

III. Research Methodology

After the basic features of the framework have been described in the previous section, the question arises how the respective relevance regarding the evaluation of IMIS is represented. To consider all relevant aspects of an IT investment decision process it is necessary to extend the existing IMIS model by an additional weighting factor. The disjunctive characteristics of the influence factors demand the selection of appropriate weighting methods. Therefore, the decision model was subdivided into a operationalisable goal hierarchy. The categorization as well as the selection process of the corresponding weighting methods is explained in the following part.

A. Characterization and Categorization of the Influence Factors

In [2], DeLone et al. divided the influencing variables of information systems into success dependent and independent. Analogous to this approach we categorized the influence factors in our framework into value-creation dependent and independent. The categorization is presented in the following section. The starting point of the considered influence factors is the IMIS evaluation model from Ulbricht et al. [38]. An overview of the extended framework is given in Figure 3.

Value-creation-dependent influence factors

This category includes the factors, which are crucial for the creation of an economic benefit. Due to the strong impact on the business success, they are particularly important for corporate decisions. These factors comprise the internal as well as the external realization conditions, e.g., the capability to realize the results from the IT-system in an appropriate time. Another influence factor in this category is the potential benefit regarding the use of IMIS. This means value-creation through faster data processing or more detailed analysis. In most cases, business value is the most important decision criteria for companies. In this consideration, this point also includes non-monetary benefits and second-level effects like an improved customer satisfaction. In addition to these stakeholder-oriented factors, this category also includes technical aspects, which are related to the value-creation. These include, for example, the frequency of change and the range of variation. One of the probably most important advantages of IMIS is the capability of fast data processing. Expert interviews and case studies in this area have shown, however, that the requirements regarding, e.g., the urgency vary significantly between different business areas. In order to achieve independence of the factors, it is important that the potential value generation is considered independent of the other factors. The independence of the decision factors is the prerequisite for the application of methods for the assessment of alternatives[42].

Value-creation-independent influence factors

This category includes factors which are of minor importance from a solely business perspective. This means that these factors have no direct relation to the value-creation. An economically oriented decision maker is in most cases not interested in the underlying data volume or the data structure. On the other hand, these factors play a very important role for the technical evaluation of In-Memory systems. In order to consider all relevant aspects for the evaluation, company representatives, scientists as well as IMIS vendors are involved in the determination of these factors.

B. Method Selection

The determination of weights in the context of information systems have already been the subject of numerous research projects. There exists a plenty of methods to define the relevance of decision alternatives. The challenge for the determination of the weightings is the complexity of the investigated influencing factors in this work. Caused by the distinct characteristics of the factors it is necessary to select appropriate methods for the particular categories. The specification of the value creation dependent weighting factors require the involvement of corporate representatives with a comprehensive understanding of the business processes. As already mentioned in the previous section the significance vary according to the regarded use case. This results in the requirement that the selected method should be easy to use and time-efficient. The value creation independent factors, are determined by technical experts in the field of IMIS. For these factors, however, other properties and corresponding requirements apply. In order to obtain reliable results it is necessary to avoid inconsistencies. At the same time, the method should be proven and well applicable. In the following section the most common procedures are presented and evaluated regarding to their suitability regarding the described requirements.

Direct Rating Method

The direct rating method [43] is a rather straight forward rating method and is applicable to almost every objective target. Given a discrete objective, the direct rating method assignes a value directly to each relevant result x_i of a discrete or nominal target size. In order to keep the evaluation effort manageable, possible alternatives are determined first. In the next step all possible result values are ordered in respect to

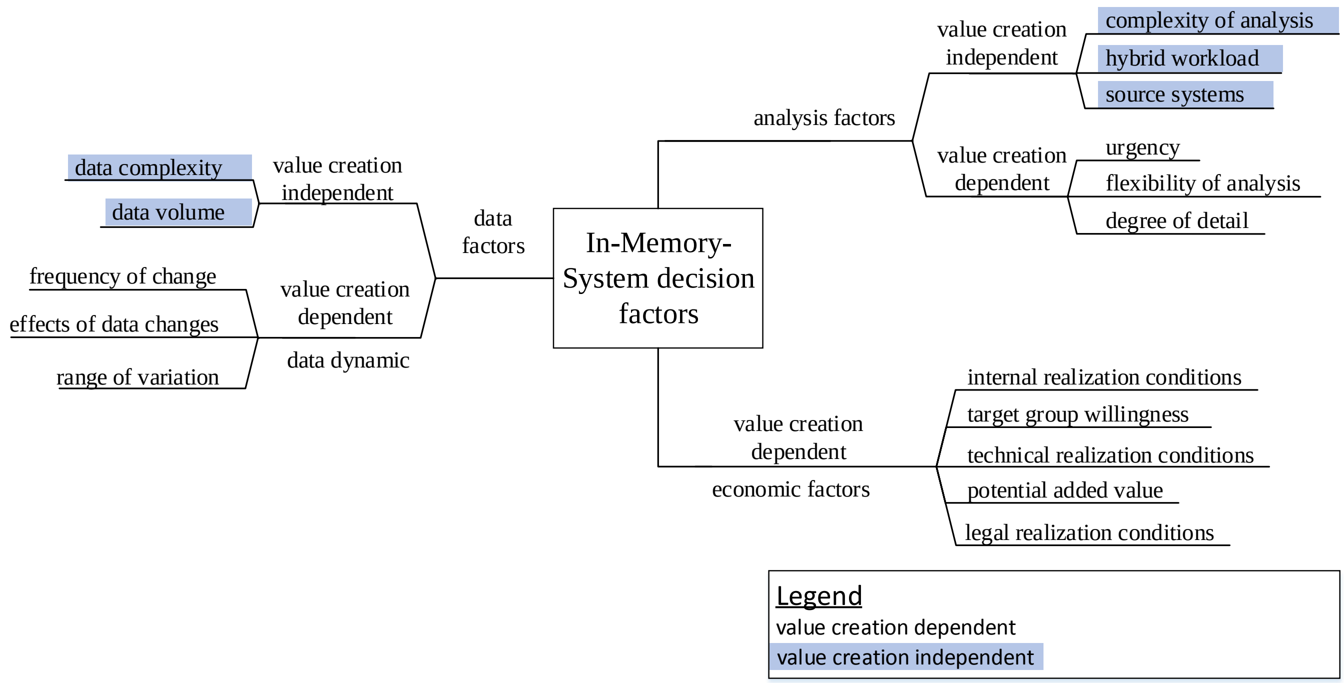

Figure 3. Overview of the analysis and evaluation framework (adapted according to [38])

the given target objective. The lowest result is assigned the lowest value of usually 0 points and the best or highest value is assigned 100 points. For all other result values in between the lowest and highest value, the person evaluating has to assign utility values in order to reflect the pre defined order. There are, however, some issues with this method since there is virtually no support given to the evaluating person on how to assign the actual values. Researchers argue that the direct rating method is more a *backup* method and should only be used in cases of missing alternatives [42]. If a direct assignment is difficult, e.g., for subjective target objectives such as image or taste, proxy attributes should be considered.

Point Allocation Method

In the point allocation method, the decision maker has a given *budget* of points. The points are assigned to the alternatives and reflect the relative importance. For example, the decision maker may be asked to assign 100 points between four alternatives that are relevant to a particular decision. With this method the weights do not have to be normalized since the sum of all assignments has to be 100 points [44]. There is, however, a drawback in the assignment process [45]. In contrast to other methods where the decision maker will assign the value of 100 points to the best alternative and will derive the importante or value of the other alternatives by relating to 100 points, there is no such fixing point in the Point Allocation Method. Especially if there are many options or alternatives, this classification can be difficult. This is because, for example, if the sum of 100 is exceeded, all assessments must be adjusted. In contrast, the assessment of single alternative of the direct rating method has no effect on all other assessments. Jia et al. [46] showed that the point allocation and the direct rating method lead to heterogenious results in terms of the decsion weights when applied in practice.

SWING

As part of algebraic methods, the SWING method was introduced by von Winterfeldt and Edwards [47]. It requires the decision maker to make a cardinal assessments of fully defined (hypothetical) alternatives. In a first step the decision maker defines the null alternative x with all possible attribute values set to the worst possible value. In the next step, possible alternatives $y_i, i = 1..n$ with different attribute values are defined or extracted from the problem context. During a survey the respondent is asked to order all alternatives. The best alterantive y_1 is assigned 100 points and the null alternative x is assigned 0 points. Now the respondent is asked to assign points to all other alternatives $y_2..y_n$. In order to determine scale factors, the points of the second best alternative y_2 shall reflect the percentage of the perceived use gain if the respondent *swings* from the null alternative x to the alternative y_i. The best alternative y_1 was already pre-defined with 100 points. Normalized factors are derived through dividing each scale factor by the sum of all scale factors.

To assign atribute weights, the respondent is asked which attribute the respondent would like to change from worst to best, based on the null alternative x. Subsequently, the respondent is asked which attribute should be changed in the next step, until all attributes are assessed. One possible way to determine attribute weights is to set the 100 points to the highest ranked (ordered) attribute and aks the respondent to assign points to all remaining attributes as a scale of 100 points reflecting their importance. Edwards et al. [48] note that it is important to cross check the results with trade off questions, especially when cost is a possible attribute.

Direct Ranking Method

The direct ranking procedure is one of the simplest methods to determine the importance of attributes. At the same time, this method produces the least accurate results of the weight determination methods. In practical environments, the direct ranking is frequently used because of its simple and fast applicability. Compared to other procedures, it is not possible to check the consistency or plausibility of the answers. The evaluation is carried out by assigning ordinal scaled preference values. In our framework, we use a range from 1 to 10 for the scale. Due to the normalization of the values, the range of the scale is of minor importance. The weighting of the particular factors is obtained by dividing the individual preferences p_i by the total sum of the preferences. The equation for the determination of the weighting is shown in (2).

$$w_i = \frac{p_i}{\sum_{i=1}^{n} p_i} \quad (2)$$

In spite of the missing methodological variety the direct ranking method suits well for the usage in corporate environments due to its simple applicability. For these reasons, this method was selected for the determination of the value-creation dependent influence factors. To determine the independent parameters more complex methods are necessary.

Analytic Hierarchy Process

The analytic hierarchy process, developed by Saaty [49], is a widely used method for multi-criteria decision problems. This method has been applied in comparable research projects like the selection of enterprise resource planning [50] or the selection of software as a service products [51]. It uses a pairwise comparison of the alternatives to determine ratios and scale priorities. Each factor is compared with every other factor. This kind of comparison improves the decision making within sophisticated problems. On the other hand, with numerous alternatives this leads to an increasing complexity. To reduce this, the alternatives are divided into hierarchies in the AHP. A major advantage with this method is the built-in ability to check the results for inconsistencies. Through the avoidance of inconsistent answers, it is possible to obtain better results in a qualitative manner. However, this requires an increased degree of attention from the participants of a study.

Despite the relatively simple use of pairwise comparisons, the AHP method can produce reliable results. Due to the high complexity and the high demands placed on the participants, this procedure is only suitable to a limited extent for the utilization in companies. This method was selected to determine the weightings of the value-creation independent factors.

IV. Application of the Framework

In this section, we present application examples of our IMIS evaluation Framework. In the first part, we determine the weightings of the influence factors, applying the direct ranking method and the AHP. Afterwards, we demonstrate the results of the case studies. For the evaluation of the framework we conducted and analyzed 10 case studies. Thereby, a wide range of companies were involved. This includes, for example, a smaller IT service provider, a medium-sized online travel provider up to a large retailing company. The characteristics of the investigated use cases are shown in Table I. Aimed by the characteristics the evaluation process becomes more comprehensible.

A. Weightings for the Value-Creation Dependent Factors

To determine the business-related significance of the value-creation dependent factors, it was necessary to include only experts with an appropriate extent of knowledge in the field of data analytics. Therefore, we asked senior corporate representatives in analytic-aware IT positions to rank the importance of each IMIS influence factor. The application of our framework is shown in more detail based on 3 selected use cases. The sample use cases have been chosen considering their business and technical characteristics. In doing so, it is possible to illustrate all aspects of a IMIS use case evaluation. The resulting weightings of the use cases are shown in Table II.

It becomes clear that the significance of the influence factors vary only a bit in the analysis and data categories. Significant differences can be seen within the economic factors. As expected, the potential added value is the most important attribute. Nevertheless, the weightings varies quite strongly. The relatively high influence of the other factors illustrates the need for an overall assessment.

B. Weightings for the Value-Creation Independent Factors

As already mentioned in Section III-B, the mainly technologically driven factors are more complex in their examination. A one-sided investigation from a business perspective does not cover all relevant aspects. It is necessary to involve a broad field of knowledge and experience in this consideration. For this reason, we have included business experts, scientists and experts from system providers to determine these factors. The involved corporate representatives originated from the high-tech industry, the retail sector and online retailing. All these branches are characterized by their high demands regarding the data processing. The representatives have been selected according to their knowledge and experiences in the area of data analytics. The scientific experts were selected from the related work in the context of IMIS. To avoid a technical bias in the investigation the participants from the IMIS system vendors have both, knowledge in the development of such systems but also experiences with the practical application and the customer needs.

A strength of the AHP method is the possibility to detect inconsistent answers. In overall the AHP process includes four phases: the decomposition, the comparative judgements, the determination of priorities and the consistency checking. For a better comprehensibility the proceeding of the AHP as well as an extraction of the results are explained in the following part:

Decomposition

During the decompensation, the underlying decision problem is subdivided into a hierarchical goal system. This step reduces the complexity of the decision-making process. In our example the decomposition is already done through the structuring of the framework into analysis, data and economic factors. Additionally, the elements of the categories were subdivided into value creation dependent and independent.

Comparative Judgements

In the second step the decision criteria are compared pairwise. This comparison is based on a 1 to 9 scale. Where a rating of 1 indicates the equal importance of the considered criteria and a score of 9 indicates the absolute dominance of an attribute over the other. The further meanings of the judgement scale can be found in Table III.

The result of the pairwise comparison is a matrix A with the relative importance of the criterias. In the case of the evaluation

TABLE I. Characteristics of the analyzed Use Cases

		Local Weight Use Case 1	**Local Weight Use Case 2**	**Local Weight Use Case 3**	**Local Weight Use Case 4**	**Local Weight Use Case 5**	**Local Weight Use Case 6**	**Local Weight Use Case 7**	**Local Weight Use Case 8**	**Local Weight Use Case 9**	**Local Weight Use Case 10**
Category	**Factor**	**Analysis of POS-Data**	**Real-Time Reporting**	**Finance Reporting**	**Transaction logging for websites**	**Analysis of strategic business decisions**	**Real-time analysis of inventory and sales data**	**Monitoring and managemen t of IT infrastructu re**	**Project planning**	**Automated financial accounting**	**Control of promotions**
Analysis	Urgency	Few minutes	Near real-time	Near real-time	few minutes	few hours	near real-time	real time	near real-time	few minutes	real time
	Flexibility of analysis	Ad-hoc	Standard	Standard	Standard	Standard	Standard	-	Standard	Standard	Standard
	Degree of detail	Medium	Very detailed	High	Medium	detailed	detailed	detailed	Very detailed	Very detailed	Medium
	Hybrid workload	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes
	Complexity of analysis	High	Very high	Medium	Low	Medium	High	Very low	High	High	Low
	Source systems	2	1	2	2	2	3	2	1	3	2
Data	Data volume	Extremely high	Extremely high	Medium	Medium	Medium	Very high	Very high	Medium	Very high	Very high
	Data complexity	Low	Relatively low	Relatively low	Low	Medium	Relatively low	Relatively low	Medium	Relatively low	Low
	Data dynamic										
	Frequency of change	Rarely	Frequently	Frequently	Frequently	Regularly	Regularly	Very frequently	Frequently	Rarely	Frequently
	Effects of data changes	Low	High	High	Low	Medium	Medium	Medium	Medium	Low	Low
	Range of variation	Moderate	Strong changes	Moderate	Little changes	Little changes	Strong changes	Strong changes	Moderate	Moderate	Little changes
Economic	Internal realization conditions	Months or longer	Hours	Days	Days	Months or longer	Days	Months or longer	Not predictable	Immediate	Immediate
	Potential added value	High	Very high	Medium	Low	High	High	High	Very high	High	Very low
	Target group willingness	Medium	High	Medium	Not predictable	Medium	High	High	Very high	High	Medium
	Technical realization conditions	Low	Low	Medium	Low	High	Low	Not predictable	Low	Low	Very high
	legal realization conditions	Relatively low	Low	High	Not predictable	Relatively low	Relatively low	Relatively low	High	Not predictable	Not predictable

TABLE III. AHP Judgement Scale

Intensity of Importance	Definition
1	Equal Importance
3	Moderate Importance
5	Strong Importance
7	Very strong Importance
9	extreme Importance

of IMIS criterias we asked experts in this area to judge the importance of the value creation independent decision factors. A partial result of the assessment can be seen in Table IV. This example shows for instance, that the expert assesses the importance of processing hybrid workload much higher than the complexity of analysis.

TABLE IV. Sample Results of the AHP

	Complexity	Hybrid Workload	Source Systems
Complexity	1	1/5	1/3
Hybrid Workload	5	1	3
Source Systems	3	1/3	1

Determination of Priorities

For the calculation of the weights the results of the comparison (matrix A) are initially normalized. Thereby, the values are divided by the sum of the respective column values. Formally this relation is shown in (3). In Table V, the results of the calculations are demonstrated based on the continued example. Thereby, it becomes clear that the weightings reflect

TABLE II. WEIGHTINGS OF THE VALUE-CREATION DEPENDENT FACTORS

Category	Factor	Local Weight Use Case 1	Local Weight Use Case 2	Local Weight Use Case 3	Local Weight Use Case 4	Local Weight Use Case 5	Local Weight Use Case 6	Local Weight Use Case 7	Local Weight Use Case 8	Local Weight Use Case 9	Local Weight Use Case 10
Analysis	Urgency	0.306	0.316	0.304	0.417	0.267	0.305	0.414	0.317	0.313	0.407
	Flexibility of analysis	0.421	0.367	0.353	0.322	0.376	0.39	0.401	0.366	0.374	0.389
	Degree of detail	0.272	0.316	0.342	0.261	0.357	0.305	0.184	0.317	0.313	0.204
Data	Data dynamic										
	Frequency of change	0.286	0.333	0.300	0.366	0.331	0.398	0.331	0.426	0.452	0.452
	Effects of data changes	0.286	0.333	0.400	0.513	0.541	0.487	0.541	0.464	0.443	0.443
	Range of variation	0.429	0.333	0.300	0.121	0.128	0.115	0.128	0.11	0.105	0.105
Economic	Internal realization conditions	0.177	0.204	0.239	0.301	0.207	0.197	0.216	0.182	0.204	0.193
	Potential added value	0.431	0.442	0.324	0.163	0.393	0.373	0.293	0.493	0.442	0.471
	Target group willingness	0.104	0.119	0.140	0.177	0.121	0.115	0.127	0.107	0.119	0.113
	Technical realization conditions	0.190	0.219	0.257	0.323	0.222	0.211	0.232	0.195	0.219	0.207
	legal realization conditions	0.098	0.017	0.039	0.035	0.056	0.104	0.132	0.024	0.016	0.015

the already observed domination of the hybrid workload towards the complexity of analysis.

$$\overline{a}_{ij} = \frac{a_{ij}}{\sum\limits_{k=1}^{n} a_{kj}} \tag{3}$$

$$\overline{a}_{11} = \frac{1}{1+5+3} \approx 0.111 \tag{4}$$

TABLE V. Sample Calculation of the Weightings

	Complexity	Hybrid Workload	Source Systems	Weight
Complexity	0.111	0.130	0.077	0.106
Hybrid Workload	0.556	0.652	0.692	0.633
Source Systems	0.333	0.217	0.231	0.260

Subsequently, the targeted weightings are determined by averaging the results. The elements are computed as follows:

$$w_i = \frac{\sum\limits_{k=1}^{n} \overline{a}_{ik}}{n} \tag{5}$$

$$w_1 = \frac{0.111+0.130+0.077}{3} = 0.106 \tag{6}$$

Calculation of the Consistency

The possibility to detect inconsistent answers helps to ensure the quality of the results. Judgements of persons are often not completely consistent. Especially in complex decision situations the individual judgements do not conform perfectly. The AHP method includes techniques for the detection of contradictory answers. The consistency ratio (CR) calculates the relation between the consistency index (CI) of the matrix and the random index (RI). The equation for the calculation of the consistency index as well as the results of the continued example from the part before can be seen below. The term λ_{max} represents thereby the maximum eigenvalue of the matrix A [52].

$$CI = \frac{(\lambda_{max} - n)}{n-1} \tag{7}$$

$$CI = \frac{(3.039-3)}{3-1} = 0.0195 \tag{8}$$

In the final step, the consistency ratio is calculated. The included term RI is an consistency index for randomly chosen results. It is assumed that the random results are highly inconsistent. The consistency ratio thus compares the quality of the examined example with the quality of arbitrary results. The corresponding values for RI are provided by Saaty in [53], as shown in Table VI.

TABLE VI. Random Indices for different sizes of matrices

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

The unanimous opinion about the consistency is that only answers with a consistency ratio lower or equal 0.1 are considered. In the example shown equation (10), the consistency ratio is about 0.034 and thus can be accepted. Throughout the investigation in overall two data sets had to be revised, due to the exceeding of the consistency ratio.

$$CR = \frac{CI}{RI} \tag{9}$$

$$CR = \frac{0.0195}{0.58} \approx 0.034 \tag{10}$$

The aggregated results of the AHP in Table VII reveal that for the evaluation of the value-creation independent analysis factors the complexity of analysis and the hybrid workload have the main impact. The amount of source systems is in this context only of minor importance. A more notable tendency can be seen between the data volume and the data complexity. The results of this category show, that the significance of the data volume is much higher in comparison to the data complexity.

TABLE VII. WEIGHTINGS OF THE VALUE-CREATION INDEPENDENT FACTORS

Category	Subcategory	Subcategory Weight	Factor	Local Weight
Analysis	Value-Creation independent	0.38	Complexity of analysis	0.42
			Hybrid workload	0.44
			Source systems	0.14
	Value-Creation dependent	0.62		
Data	Value-Creation independent	0.55	Data volume	0.81
			Data complexity	0.19
	Value-Creation dependent	0.45		

C. *Evaluation Examples*

In the following part, we will apply and interprete the results of the IMIS framework based on three selected use cases. The first chosen example comes from an early adopter of IMIS systems. The analysis of point of sales data in the retail section is one of the first examples in this area. The company participating in our case study is a leading retailer in Germany. For reasons of space and legibility we only show some key attributes of the example. The major goal for the use of an IMIS was the analysis of sales and inventory figures. The use case demands, besides current sales figures, the consideration of fluctuations due to promotions as well as external influences, like the weather conditions. The example is characterized by a high demand regarding the urgency, data volume and the complexity of analysis. The extensive and unpredictable variations of the sales figures require a very fast recognition of anomalies. The calculation includes transactional as well as analytical tasks. Despite, the rare and minor data changes the overall assessment of the data requirements is quite high. This is due to the extremely high volume of data combined with the high weight of this category. The economic evaluation reveal that the most important obstacle concerning the realization of the potential added value is the long implementation duration.

The second example is a real-time reporting case from the insurance sector and is characterized by very high requirements in the analysis as well as in the data area. For this use case, it is necessary that the results are based on up-to-date data and are processed in near real-time. The analyzes are based on large amounts of data directly from the transaction system. The case is characterized by high demands in terms of urgency, degree of detail and the complexity of the analysis. The same accounts for the data factors, showing a extreme high data volume, frequent changes in the data, high effects of the data change and strong changes in the range of variations. From an economic point of view, this case is characterized by a very high added value and a high target group willingness. There are neither internal nor external obstacles that avoid the realization of the results. For these reasons, this example is assessed very high in all categories.

The last example shows very clearly the diverging significance of the influencing factors. The use case comes from a supplier company in the medical field. This company uses IMIS to improve their financial and controlling reports. Despite relatively small changes to the data base, it is important that the data is up-to-date and the results of the analyzes are available very quickly. In comparison to the other use cases, the overall technical requirements are on a lower level. The same is true for the economical factors. Especially the high legal regimentation stifle/obstruct the economical assessment.

For a better clarity and easier interpretation, we assigned the results of the use case evaluation to a portfolio chart (Figure 4). This chart is comparable to the strategic portfolio matrix of the Boston Consulting Group [54]. The advantage of this representation is the possibility to have a visual indicator for the evaluation of the complex underlying decision problem. The dimensions of the chart are based on the categories of the presented framework. The analysis and data requirements built the axes of the chart. The radius of the data points reflect the economical assessment. The chart is an easy to use tool to indicate promising use cases. The provided example is based on the assessment of 10 use cases, as seen in Table I.

As mentioned at the beginning of this contribution the total utility is calculated using the weighted sum model (11) of the multi-criteria decision making. The calculations of the final metrics is shown for the analysis requirements of use case 1. The weightings are based on the results from the direct ranking and the AHP method (see Sections IV-A and IV-B). The system requirements (x_i) are represented by the results of the use case assessment (as seen in Table I). For the calculation, the assessment have been decoded. The answers are based on a ordinal scale and therefore they can be easily transformed. The sample calculation is shown in (11).

$$\begin{aligned} U_A = 0.62 \times (0.31 \times 3 + 0.42 \times 5 + 0.27 \times 3) \\ +0.38 \times (0.42 \times 4 + 0.44 \times 5 + 0.14 \times 4) \\ = 4.21 \end{aligned} \tag{11}$$

An interpretation of the calculation only makes sense in comparison to the other results. The visualization indicates that the evaluation of the use cases is quite diverse. The use case *Finance Reporting* for instance, may be characterized by a rather low economical assessment on one side, having medium to low data and analytical requirements on the other side. Although an evaluation of a use case scenario is still subjective to the decision maker's assumptions and weights, the chart provides a tool to either choose, rule out or change

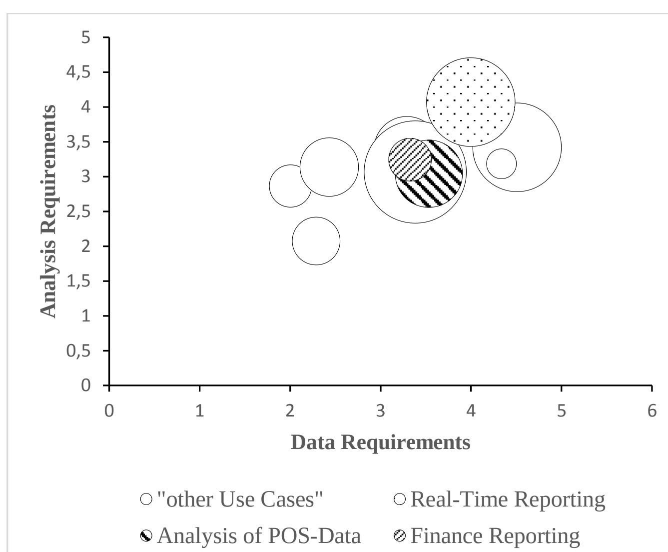

Figure 4. Visualization of the evaluation results

possible use cases. This may also lead to the decision to only use IMIS in parts of the originally planned scenario or to switch to substitute technologies. The process of the application scenario definition, which could be a repetitive process, is also supported by the framework.

V. Conclusion

Recent research as well as practical applications of In-memory systems have shown a research gap concerning the structured consideration of IMIS use cases. The aim of this work was the development of a flexible framework for the evaluation of IMIS use cases. Previous IMIS examples have shown a varying importance of the individual influencing factors. To address these variations the decision factors were subdivided into the categories value-creation dependent and value-creation independent. The methods for the determination of the weightings were selected according to these categories and the characteristics of the factors. The weightings of the value creation dependent attributes are determined by the direct ranking method for each investigated use case. For the weightings of the technology oriented, value creation independent factors the analytic hierarchy process was applied. In order to map all factors and their significance to the additive model of the multi-criteria decision making was applied. The presented framework allows to examine existing, as well as exemplary future use cases with regard to the influence factors of In-memory based IT systems. The approach considers both, the system requirements and their corresponding importance. This enables decision-makers to investigate IMIS scenarios for their application potential.

In future work, the framework should be extended to other industries. A broad selection framework is also conceivable that shows reasonable conditions for the use of the In-memory technology. With the aid of the framework, catalogs could be created for suitable and tested application scenarios.

References

[1] S. Ulbricht, M. Opuszko, J. Ruhland, and S. Gehrke, "A use case-oriented framework for the evaluation of in-memory it-systems," in The Sixth International Conference on Data Analytics, 2017, pp. 6–11.

[2] W. H. DeLone and E. R. McLean, "Information systems success: The quest for the dependent variable," Information systems research, vol. 3, no. 1, 1992, pp. 60–95.

[3] J. Peppard and J. Ward, "Beyond strategic information systems: towards an is capability," The Journal of Strategic Information Systems, vol. 13, no. 2, 2004, pp. 167–194.

[4] "Top 10 Hot Big Data Technologies," 2016, URL: https://www.forbes.com/sites/gilpress/2016/03/14/top-10-hot-big-data-technologies/ [accessed: 2017-07-11].

[5] "SAP fehlen echte HANA-Business-Cases," 2015, URL: http://www.cio.de/a/sap-fehlen-echte-hana-business-cases,2940526 [accessed: 2017-07-24].

[6] "Lack of SAP HANA use cases stifling demand among ASUG members," 2014, URL: http://diginomica.com/2014/08/08/lack-sap-hana-use-cases-stifling-demand-among-asug-members/ [accessed: 2017-07-24].

[7] "SAP Business Suite powered by SAP HANA," 2014, URL: https://www.pac-online.com/download/9757/125462 [accessed: 2017-07-12].

[8] G. Piller and J. Hagedorn, "Business benefits and application capabilities enabled by in-memory data management." in IMDM, 2011, pp. 45–56.

[9] R. Schütte, "Analyse des einsatzpotenzials von in-memory-technologien in handelsinformationssystemen." in IMDM, 2011, pp. 1–12.

[10] H. Garcia-Molina and K. Salem, "Main memory database systems: An overview," IEEE Transactions on knowledge and data engineering, vol. 4, no. 6, 1992, pp. 509–516.

[11] D. J. DeWitt, R. H. Katz, F. Olken, L. D. Shapiro, M. R. Stonebraker, and D. A. Wood, "Implementation techniques for main memory database systems," in Proceedings of the 1984 ACM SIGMOD Conference, vol. 14, no. 2. ACM, 1984, pp. 1–8.

[12] F. Färber, S. K. Cha, J. Primsch, C. Bornhövd, S. Sigg, and W. Lehner, "Sap hana database: data management for modern business applications," ACM Sigmod Record, vol. 40, no. 4, 2012, pp. 45–51.

[13] D. J. Abadi, P. A. Boncz, and S. Harizopoulos, "Column-oriented database systems," Proceedings of the VLDB Endowment, vol. 2, no. 2, 2009, pp. 1664–1665.

[14] D. Abadi, S. Madden, and M. Ferreira, "Integrating compression and execution in column-oriented database systems," in Proceedings of the 2006 ACM SIGMOD international conference on Management of data. ACM, 2006, pp. 671–682.

[15] H. Plattner and A. Zeier, In-memory data management: technology and applications. Springer Science & Business Media, 2012.

[16] H. Plattner, "A common database approach for oltp and olap using an in-memory column database," in Proceedings of the 2009 ACM SIGMOD International Conference on Management of data. ACM, 2009, pp. 1–2.

[17] A. Kemper and T. Neumann, "Hyper: A hybrid oltp&olap main memory database system based on virtual memory snapshots," in Data Engineering (ICDE), 2011 IEEE 27th International Conference on. IEEE, 2011, pp. 195–206.

[18] N. May, A. Böhm, and W. Lehner, "Sap hana–the evolution of an in-memory dbms from pure olap processing towards mixed workloads," Datenbanksysteme für Business, Technologie und Web (BTW 2017), 2017.

[19] P. Loos, J. Lechtenbörger, G. Vossen, A. Zeier, J. Krüger, J. Müller, W. Lehner, D. Kossmann, B. Fabian, O. Günther et al., "In-memory-datenmanagement in betrieblichen anwendungssystemen," Wirtschaftsinformatik, vol. 53, no. 6, 2011, pp. 383–390.

[20] M. Pezzini, D. Feinberg, N. Rayner, and R. Edjlali, "Hybrid transaction/analytical processing will foster opportunities for dramatic business innovation," Gartner (2014, January 28) Available at https://www. gartner. com/doc/2657815/hybrid-transactionanalytical-processing-foster-opportunities, 2014.

[21] F. Özcan, Y. Tian, and P. Tözün, "Hybrid transactional/analytical processing: A survey," in Proceedings of the 2017 ACM International Conference on Management of Data. ACM, 2017, pp. 1771–1775.

[22] J. Krueger, M. Grund, C. Tinnefeld, B. Eckart, A. Zeier, and H. Plattner, "Hauptspeicherdatenbanken für unternehmensanwendungen," Datenbank-Spektrum, vol. 10, no. 3, 2010, pp. 143–158.

[23] P. Loos, S. Strohmeier, G. Piller, and R. Schütte, "Comments on in-memory databases in business information systems," Business & Information Systems Engineering, vol. 4, no. 4, 2012, pp. 213–223.

[24] D. J. Abadi, "Query execution in column-oriented database systems," Ph.D. dissertation, Massachusetts Institute of Technology, 2008.

[25] J. Krueger, M. Grund, C. Tinnefeld, H. Plattner, A. Zeier, and F. Faerber, "Optimizing write performance for read optimized databases," in International Conference on Database Systems for Advanced Applications. Springer, 2010, pp. 291–305.

[26] T. Winsemann and V. Köppen, "Kriterien für datenpersistenz bei enterprise data warehouse systemen auf in-memory datenbanken." in Grundlagen von Datenbanken, 2011, pp. 97–102.

[27] R. Meyer, V. Banova, A. Danciu, D. Prutscher, and H. Krcmar, "Assessing the suitability of in-memory databases in an enterprise context," in Enterprise Systems (ES), 2015 International Conference on. IEEE, 2015, pp. 78–89.

[28] G. Piller and J. Hagedorn, "In-memory data management im einzelhandel: Einsatzbereiche und nutzenpotentiale," in Multikonferenz Wirtschaftsinformatik, 2012.

[29] ——, "Einsatzpotenziale für in-memory data management in betrieblichen anwendungssystemen," Wirtschaftsinformatik & Management, vol. 3, no. 5, 2011, pp. 18–25.

[30] R. Winter, S. Bischoff, and F. Wortmann, "Revolution or evolution?

reflections on in-memory appliances from an enterprise information logistics perspective." in IMDM, 2011, pp. 23–34.

[31] J. vom Brocke, S. Debortoli, and O. Müller, "In-memory database business value," 360 - The Business Transformation Journal, vol. 3, no. 7, 2013, pp. 16–26.

[32] J. vom Brocke, "In-memory value creation, or now that we found love, what are we gonna do with it?" BPTrends, vol. 10, 2013, pp. 1–8.

[33] J. vom Brocke, S. Debortoli, O. Müller, and N. Reuter, "How in-memory technology can create business value: insights from the hilti case," Communications of the Association for Information Systems, vol. 34, no. 1, 2014, pp. 151–167.

[34] R. Bärenfänger, B. Otto, and H. Österle, "Business value of in-memory technology–multiple-case study insights," Industrial Management & Data Systems, vol. 114, no. 9, 2014, pp. 1396–1414.

[35] C. Cundius and R. Alt, "A process-oriented model to business value–the case of real-time it infrastructures," in Proceedings of the 50th Hawaii International Conference on System Sciences, 2017.

[36] ——, "Real-time or near real-time?-towards a real-time assessment model," Thirty Fourth International Conference on Information Systems, 2013.

[37] L. Olsson and C. Janiesch, "Real-time business intelligence und action distance: Ein konzeptionelles framework zur auswahl von bi-software." in Wirtschaftsinformatik, 2015, pp. 691–705.

[38] S. Ulbricht, M. Opuszko, J. Ruhland, and M. Thrum, "Towards an analysis and evaluation framework for in-memory-based use cases," in The Twelfth International Multi-Conference on Computing in the Global Information Technology, 2017, pp. 22–27.

[39] E. Triantaphyllou, Multi-criteria decision making methods. Kluwer Academic Publishers, Dordrecht, 2000.

[40] A. R. Hevner, S. T. March, J. Park, and S. Ram, "Design science in information systems research," MIS quarterly, vol. 28, no. 1, 2004, pp. 75–105.

[41] A. R. Hevner, "A three cycle view of design science research," Scandinavian journal of information systems, vol. 19, no. 2, 2007, p. 4.

[42] R. Klein and A. Scholl, Planung und Entscheidung. Vahlen, München, 2004.

[43] D. Von Winterfeldt and W. Edwards, "Decision analysis and behavioral research," Cambridge, MA (USA) Cambridge Univ. Press, 1993.

[44] P. Goodwin and G. Wright, Decision analysis for management judgment. Wiley, 1998.

[45] J. R. Doyle, R. H. Green, and P. A. Bottomley, "Judging relative importance: direct rating and point allocation are not equivalent," Organizational behavior and human decision processes, vol. 70, no. 1, 1997, pp. 65–72.

[46] J. Jia, G. W. Fischer, and J. S. Dyer, "Attribute weighting methods and decision quality in the presence of response error: a simulation study," Journal of Behavioral Decision Making, vol. 11, no. 2, 1998, pp. 85–105.

[47] W. Edwards and D. von Winterfeldt, "Decision analysis and behavioral research," Cambridge University Press, vol. 604, 1986, pp. 6–8.

[48] W. Edwards, R. Miles, and D. von Winterfeldt, Advances in Decision Analysis: From Foundations to Applications. Cambridge University Press, 2007.

[49] T. L. Saaty, "What is the analytic hierarchy process?" in Mathematical models for decision support. Springer, 1988, pp. 109–121.

[50] C.-C. Wei, C.-F. Chien, and M.-J. J. Wang, "An ahp-based approach to erp system selection," International journal of production economics, vol. 96, no. 1, 2005, pp. 47–62.

[51] M. Godse and S. Mulik, "An approach for selecting software-as-a-service (saas) product," in Cloud Computing, 2009. CLOUD'09. IEEE International Conference on. IEEE, 2009, pp. 155–158.

[52] M. Kwiesielewicz and E. Van Uden, "Inconsistent and contradictory judgements in pairwise comparison method in the ahp," Computers & Operations Research, vol. 31, no. 5, 2004, pp. 713–719.

[53] T. L. Saaty, "The analytic hierarchy process: planning, priority setting, resources allocation," New York: McGraw, vol. 281, 1980.

[54] D. C. Hambrick, I. C. MacMillan, and D. L. Day, "Strategic attributes and performance in the bcg matrix a pims-based analysis of industrial product businesses," Academy of Management Journal, vol. 25, no. 3, 1982, pp. 510–531.