KPI-based decision impact evaluation system for adaptive business intelligence

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ABSTRACT. *Nowadays, there is an approved concept called Business Intelligence that supports the decision making process. By extending Business Intelligence, a new concept called Adaptive Business Intelligence has been emerged. The current state in Adaptive Business Intelligence (ABI) is that decisions are not evaluated in a periodic manner and the inappropriate decisions of the past might occur again. The enhancement of decision quality is one of the major outputs behind this article. The evaluation of past decisions makes it helpful to take future complex decisions based on the uncertainty or confusion of historical decisions. The adaptability behind the proposed solution is achieved through the evaluation, tracking and recommendation of decisions in any Business Intelligence system. This article presents a reference architecture for a new approach called KPI-based decision impact evaluation system for adaptive business intelligence that can enrich the ABI applications.*

RÉSUMÉ. *Aujourd'hui la Business Intelligence (BI) est un concept bien mature et approuvé. Le rôle de la BI est de soutenir le processus de la prise de décision. Dans le cadre de tentative d'extension et d'amélioration de la BI, un nouveau concept appelé Adaptive Business Intelligence (ABI) a émergé. L'état actuel de l'ABI ne permet pas l'évaluation périodique des décisions prises, et les mauvaises décisions du passé peuvent encore se reproduire. L'amélioration de la qualité de la décision est l'un des principaux avantages du concept présenté dans ce papier. L'évaluation des décisions prises devient utile afin d'améliorer les décisions futures. L'adaptabilité dans la solution proposée est obtenue par le suivi des évaluations et la recommandation des décisions. Cet article présente une architecture de référence pour une nouvelle approche appelée système d'évaluation de l'impact de la décision au sein de l'ABI qui permet d'enrichir les applications ABI existantes.*

KEYWORDS: *Business intelligence, adaptive business intelligence, decisions, evaluation.*

MOTS-CLÉS: *business intelligence, adaptive business intelligence, décisions, évaluation.*

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1. Introduction

Significant numbers of companies are facing different types of challenges because of the increasing amount of data produced internally and externally. Such challenges are touching almost all parts of a typical business organization - IT, management, human resources, etc. For example, the list of the technical challenges that should be addressed at the first row are not limited only by the ability of particular company to store enormous amounts in an error-prone way, such list also includes an ability to collect, manage, filter and analyze data, in a sense that abovementioned facilities provide the best possible image of the business situation of particular company on strategic, tactical and most influenced operational levels. In order to ensure correct strategic and operational decisions, a decision-knowledge must be gained and/or derived from an available data. Initially, those challenges motivated the development of a Business Intelligence (BI) concept, which its primary role is to support decision makers and help them to perform better decisions based on the collected knowledge.

Software systems, which are primarily based on the concepts and ideas promoted by a BI, are known for many years. For the moment, such systems are well presented in the market and widely adapted by large enterprise players, as well as by small and medium ones. The functionality of such systems is quite advanced and even got an adaptability module integrated into a core architectural design. Usually, extensions like adaptability module are dedicated to improve the core functionality of a BI system and push their development ahead. In the particular case of the adaptability module, it is dedicated to respond to real needs of a customer (or user) and to adapt the system's behavior based on factors/metrics introduced by rapidly changing environment.

On one side, BI systems are dedicated to help decision maker to perform better decisions based on knowledge provided by a system, own experience and evolving circumstances (e.g., environment changes). On the other side, besides performing decisions, it is quite important to know the impact of a decision. For instance, an evaluation of past decisions leads to perform more optimal future decisions by gathered experience from performing and executing decisions in the past. Such approach will optimize the taken decisions and help to minimize, or at least significantly reduce uncertainty and confusion existed in the past when the previous decision was performed. For this purpose, an ongoing situation has to be categorized in order to predict appropriate decisions and/or actions. In other words, the evaluation of historical decisions is essential to make future decision in an optimal fashion.

This current work presents a new adaptability module for a BI system as an innovative approach. The adaptability module called decision evaluation system within adaptive business intelligence and it can enrich the traditional adaptive BI applications. Besides presenting the module and its underlying principal architecture, the current work also demonstrates the usage of statistical methods and approaches (e.g. correlations), which are located at the core components of the proposed adaptability module.

The organization of this article is as follows: Section two gives the main background information about Business Intelligence, self-adaptive systems, and the use of adaptability in the BI systems. In addition we will talk about the decision making process in general. In section three, the process of the decision evaluation system will be explained. Section four shows the reference architecture of the decision evaluation system within ABI with its characteristics and components. After that, the steps followed to implement a prototype that illustrates the new adaptive business intelligence system are detailed in section five. Section six presents the results of a survey conducted to show the demand for functionalities offered within proposed ABI architecture. The article then concludes with a brief summary regarding the contribution of this content and gives an outlook to the future directions.

2. Adaptive Business Intelligence

2.1. Business Intelligence

The BI concepts widely adopted in industry and well explored by the academia. The main motivator to implement ideas behind BI into a software system is to enable decision maker with the required knowledge to perform optimal decisions. Knowledge, which is usually offered to decision maker, is based on an extracted information from various structured, semi-structured or unstructured data sources like data warehouses (DWHs), ERP systems, Web Services, CRM systems, flat files, third party systems, etc. In order to provide a decision maker with required knowledge, the data is first of all loaded into a dedicated central multi-dimensional data warehouse, and later on processed be means of online analytical processing(OLAP) analysis, reports or other types of data investigations techniques. After processing data in a desired way the presentation part takes place. The presentation of knowledge to the user (which is decision maker) is required in order to facilitate smoother decision making process.

In 1989, Howard Dressner from the Gartner Group introduced the BI term as an umbrella term to describe concepts and methods that are dedicated to improve business decision-making process by means of support systems, which is based on pure facts. Few years later, the definition of BI was updated by in a work of (Kemper *et al.*, 2006). Kemper *et al.* collected and identified 7 different definitions of BI. In particular, according to the work of Kemper *et al.*, BI is equal to data warehouse, alerting system, advanced management information system and list of other systems with intersecting functionality.

However, it is very important not only to treat a particular BI system as an extension of a data warehouse, and limits its role only to transfer information from an operative information system, which is in charge of transactional data, *via* Online Transaction Processing (OLTP) into a systems that supports OLAP analysis required by company's information reporting policies (Gómez *et al.,* 2008).

According to (Turban *et al.,* 2011) and (Rezaie *et al.,* 2011), BI system can be defined as "an umbrella term that encompasses tools, architectures, databases, data warehouses, performance management, methodologies, and so forth, all of which are integrated into a unified software suite or package".

A BI is considered in this work as a methodology that underlies a system, which is dedicated to support decision-making process. It consists out of many different methods and techniques. For instance, a typical process to be conducted in order to move data from various systems into a BI system is known as Extract-Transform-Load (ETL) process. Other tools, which are playing a fundamental role in the BI concept are data quality assurance, data warehousing, master data management, Web data management, and many others. Usage of BI methodology can be helpful for any actor within a particular organization. It can influence decisions made by a particular employee in an organization, regardless of her/his positions, responsibilities and assigned company's department (e.g. human resources, sales, marketing, research and development, etc.). It helps them to have an appropriate knowledge about the factors affecting their daily business routines and support them in decision making process.

Figure 1 demonstrates a typical architecture of BI system, which performs the ETL process in order to extract, transform and load data into a particular centralized data warehouse. Later on, loaded data are processed and delivered to end users in form of reports, OLAP cubes, ad-hoc queries, etc.

In order to facilitate analysis and discovery of knowledge inside a multidimensional data located inside data warehouse, which at the end should be delivered to business managers, Codd *et al.* introduced the OLAP concept and defined that with twelve rules respectively (Codd *et al.,* 1993). OLAP offers a possibility to explore, aggregate, and visualize data using its operators. While implementing BI concepts into a software solution, an ability to capture data required by business users is a necessary step to be made. And usually, providing an appropriate information, which should be directly integrated into a data warehouse, is the most expensive phase in terms of time and resources. A manager, who is in charge of implementing a BI solution, has first of all to detect exact information, which could be useful for stakeholders in the decision-making process. After identifying right information required for a knowledge, which influences a decision-making process, a manager usually should perform an extract step, which includes data acquisition from heterogeneous sources (e.g., R/DBMS, ERP, excel files, flat files, etc.) in various formats. The next stages after the data extraction process can be either transformation and load or load and transformation. And the reality depends on a schema of data load chosen whether it is ETL (Extract-Transform-Load) or ELT (Extract-Load-Transform). Transformation step includes all activities related to manipulations on data done after extraction (or load). It mostly involves transformations of operational data into a specially formed data, which can be interpreted in terms of business and economy. It is a composition of several sub-processes, *i.e.* filtering (eliminating redundancies and outliers), harmonization, aggregation and enrichment (Kemper *et al.,* 2006). Loading steps are dedicated to bring the data into a central multidimensional database and/or to a data warehouse.

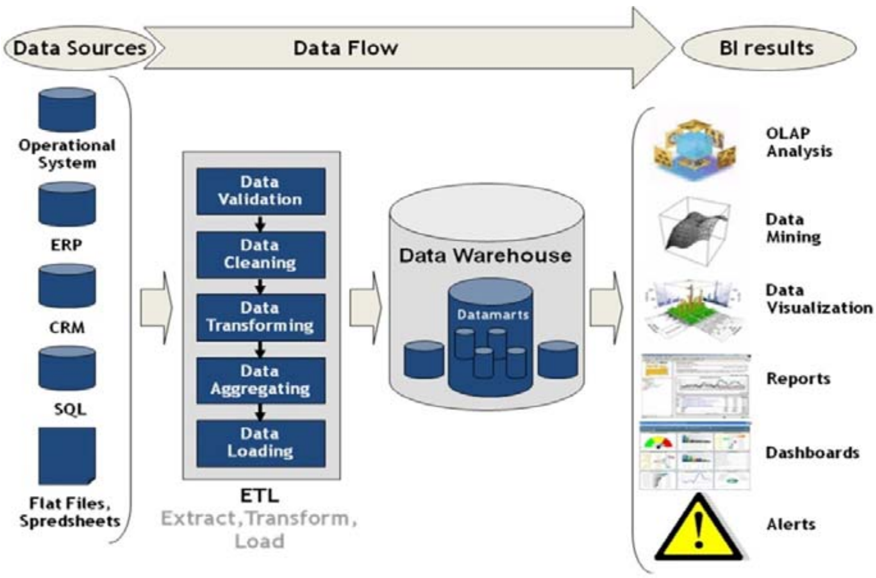

Figure 1. Business Intelligence Architecturebased on (Kimball, Ralph, 1996)

The terms that are used in a context of data warehouse are dimensions, facts, aggregations and hierarchies. Depending on business needs, the data storage schema can be implemented in a view of star, snowflake, or galaxy. Usually, data inside data warehouse are grouped into specialized data marts, which are defined in functional terms. Data marts may include subject-specific, previously aggregated, historical, current and planned data (Naana and Rezgui 2010). As it was mentioned before, in order to bring data that were pulled from various data sources in a centralized data warehouse into a form, which can be interpreted by a human, BI solutions play a big role. They help user to have different views on data, which are based on an analysis need of particular user. For instance, BI user may want to interpret her/his data in form of a pie chart, in order to illustrate numerical proportion, or she/he can use a bar chart to show comparisons among categories. Presenting information in a right form places a significant role in understaffing subjects, and as it was mentioned by (Gluchowski *et al.,* 2008) “Finally, the value of the information [...] not only depend on the offered content, but also on the chosen form of presentation.” However, besides offering functionality, BI solutions are also taking care of user experience as a whole. For instance, both data preparation and data presentation in form of reports are well presented in a various number of software solutions. However, to improve user's performance in terms of data analysis, many of BI tools are offering a user-friendly graphical interface, drag-and-drop techniques for creating ad-hoc reports and other functionalities. Those tools, which are suitable for employees being in lack of profound IT knowledge, are thus enabling them to perform evaluations without needing to forward their requests to IT specialists. Standard reports and dashboards are prebuilt functionality and are normally available out-of-the-box. They usually contain pre-calculated indicators and serve as a basis for decision-making. Another instance of information presentation is Balanced Scorecards (BSC), which describes various tasks such as activity planning, communication and inspection of Key Performance Indicators (KPIs). BSC empower users with other possibilities to perform data analysis and reporting.

2.2. Self-adaptive systems

The complexity of software systems and the rapidly changing environment led the software engineering community to look for a concept, which allows systems to adapt themselves. And usually, an adaption of particular system should be based on users' behaviors, their profiles or changes in requirements. This motivated to approach towards creation of the self-adaptive systems.

There is couple of terms defining the self-adaptive software systems. And of those definition is introduced by (Oreizy *et al.,* 1999) such as "Self-adaptive software modifies its own behavior in response to changes in its operating environment. Here operating environment means anything observable by the software system, such as end-user input, external hardware devices and sensors, or program instrumentation". Later, Villegas extended the abovementioned definition of the self-adaptive systems to the following "Such dynamic systems adapt in response to changes in their environments, either to ensure the continuous satisfaction of their functional and non-functional requirements, or to provide ubiquitous and context-dependent smart services" (Villegas Machado *et al.,* 2011).

As it may be derived from the definitions of the self-adaptive systems, one of the core properties which they bring to software components is the flexibility-by-design. And property such as flexibility is a requirement that influencing business intelligence domain and motivates researchers to change (or re-adapt) previously applied BI concepts and integrate concepts behind self-adaptive systems into them. The next section gives more details about the new generation of BI motivated by the self-adaptive software.

2.3. Adaptive Business Intelligence

The extension of BI by using adaptability based on prediction and optimization methods and techniques for forecasting and decision supporting is called Adaptive Business Intelligence (ABI) and was firstly introduced by (Michalewicz *et al.,* 2006) and enriched by multiple authors (Nenortaitė and Butleris, 2009; Fabac, 2010; Burmester, 2011 ; Lau *et al.,* 2012 and Kim *et al.,* 2013).

For instance, Michalewicz defines the term ABI as "the discipline that uses prediction and optimization techniques to build self-learning *'decisionning'* systems" (Michalewicz *et al.,* 2006, p. 5)

Adaptive Business Intelligence had been investigated by different researchers from different point of views (e.g., adaptability in user interface, adaptability in models, automatic decision making, and adaptive knowledge presentation). However, despite progress of the research in various directions, most of these initiatives are isolated from each other and does not provide a general integrated overview. And one of the most crucial points, which was ignored, is the adaptability of ABI in a content of gathers/generated knowledge (e.g., decisions), the human involvement in a decision-making process, and in the recommendation for particular better decisions, which are based on a past experience.

In the ABI systems, decisions are not evaluated in a periodic manner and the inappropriate decisions of the past might occur again and again over time in future. Such system behavior prevents companies from receiving benefits in decision-making process, which can be based on the historical pitfalls. And as it was mentioned before, introducing past experience enhances the quality of decisions made within a company over time. The same applies for archiving such decisions, which considered as "best practices" or most successful ones. Activities in storing and maintaining catalog of such decisions, and integrating them later on into a decisions recommendation system, will optimize decision for a specific issue in a company.

Management of BI decisions over time is one of the major contributions of current work. The evaluation of past decisions makes it helpful for companies to perform more optimized and efficient decisions in future. In case a company will be relaying on the experience of past decisions, it will significantly improve reduction of uncertainty and confusions existed in historical perspective when the very first similar decisions were taken. For this purpose, we need to categorize our present situation in order to predict appropriate decisions and/or actions. In other words, the evaluation of past decisions is an essential activity to perform in order to make future decisions more efficient and optimal.

Activities behind the management of past decisions of a company include storing, evaluating, and ranking of decisions. For instance, historical decisions should be stored in a central repository, which serves as a core of a new ABI concept. An adaptability behind proposed solution is achieved through decision evaluation techniques, which incorporates the analysis of correlations over already taken decisions in a BI system. Such evaluation presents gathered advanced knowledge in a way that a company will see its decisions in a format that suits its expectations and requirements. For instance, well adapted BI tools such as dashboard can be used in order to visualize each single decision taken in the past, so they can be seen on a dashboard along with the reputation of a single decision and total number of it occurrences over time.

2.4. Decision-making process

There are a significant number of researches addressing decision-making process issues. For example, as it shown on the Figure 2, Simon considered a process of decision making as a sequence of four connected principal phases: (1) finding occasions for making a decision, (2) finding possible courses of action, (3) choosing among courses of action, and (4) evaluating past choices (Simon, 1977).

Figure 2. Decision-making process, based on (Simon, 1977)

According to (Simon, 1977) the first phase consists out of the occasions that are requiring particular decision. The second phase, called design activity, involves inventing, developing and analyzing possible courses of action (e.g. target direction of decision). After that comes the third phase, called choice activity, which emphasizes on choosing a particular course of action from the available directions found during previous phase. The final phase, which is in charge of evaluating the choices made, known as review activity.

Despite a decisions making is a daily activity of many people, the steps made to achieve particular decision are still remaining invisible. It is really hard to tell what exactly going on inside the minds of managers in charge of performing decisions. It is very difficult to understand a document or to improve a decision process. For many organizations, a managerial decision is treated as a “black box” and totally not transparent. It is not a subject explanation or review and we should admit that human decision-making process is invisible (March, 1987; Davenport *et al.,* 2001, Kahneman, 2003, p. 131)

According to the Turban *et al.* “decision making” is a process of choosing among two or more alternative courses of action for the purpose of achieving one or more goals (Turban *et al.,* 2011, p. 42)

BI systems try to assist decision-makers in their tasks. Traditional decision making process is defined as the process, which manages various flows of data in order to transform data into information, and then into knowledge. So far, this process deals only with the first phase (Simon, 1977). All of the other three phases, which come after, are taken only by humans, without any kind of assistance from ICT side. The software is able to automate knowledge generation process, whether a human performs her/his decision based on provided knowledge or not. The decision itself is not supported by the BI system; it is only making the knowledge available to a human.

Adaptive Business Intelligence Systems (ABIS) are step ahead and cover the following phases of Simon's approach:

– finding occasions for making a decision,

– finding possible courses of action, and

– choosing among courses of action.

However they only cover these phases only partially and the support of the fourth step is missing.

Currently, the actual ABIS have following limitations:

– Fully-automated approaches, decision-making is done by systems itself without human contribution;

– Underestimated decision evaluation techniques;

– Limited decision impact simulation, one dimensional impact (e.g. measurement of the impact on single KPI);

– Anonymous decision responsibility and

– Missed knowledge:

- KPI to KPI impact relationships;
- KPI to decision impact relationship and
- Evaluation and reputation of the decision made.

All of the abovementioned issues can be solved (to some extent) by introducing the evaluation of decisions within a particular company's BI solution.

3. Decision evaluation process

The proposed decision evaluation process includes storing, recommendation, evaluation and ranking of BI decisions. These decisions are stored in a central repository that serves as a core of the new adaptive BI system. On one hand, the proposed system adapts the decisions raking and recommendations based on their evaluation and on the other hand, it adapts the decision recommendation based on user responsibilities. All of the made decisions should be categorized according to specific domains (e.g. sales/presales decisions, marketing decisions, logistic decisions, productions decisions, human resources decisions, political decisions, etc.).

The adaptability behind the proposed solution is achieved through decision evaluation techniques, which incorporate the analysis of correlations over already taken decisions in a BI system. Such evaluation presents gathered advanced knowledge in a way that a company will see its decisions in format that suits expectations and requirements of a company. For instance, well adapted BI tools such as dashboards can be used in order to visualize each single decision taken in the past, so they can be seen on a dashboard along with reputation of a single decision and total number of it occurrences over time.

The proposed approach differentiates between "first-level" knowledge and "advanced level" knowledge. The "first-level" knowledge is widely used by the traditional BI/ABIS. It transforms data into knowledge and presents gathered knowledge to the end users in order to help her/him in her/his decisions. It is basically data manufactory with the goal to help users to get the right knowledge. Normally, the offered knowledge to end users does not include information about the decision itself (evaluation, decision-maker, decision time and impacted domain). The extended version of the "first-level" knowledge, the "advanced" knowledge, includes the knowledge provided by the first-level and extends it with the knowledge about the decision.

The proposed ABIS concept distributes the decision between two primary actors: ABI end users and ABI system. Human machine interaction is very valuable for the effectiveness of the decisions. The most important added value within the proposed ABI system is the decision database component. This will relieve the loss of knowledge acquired from past decisions.

The following cross-functional Flowchart diagram, shown on the Figure 3, represents the process of the proposed ABI system and the interactions between them and the end users. Let us first explain the schema. Every successful business is built based on objectives, which can be usually measured. Such measurable objective is called key performance indicators (KPI). The user is only capable of selecting, describing and identifying KPIs in order to monitor them. From this description, the system will generate a KPI matrix, and store it into a decision database that will be used later. This matrix tries to gives responses to the following questions:

– What is the level of this KPI (strategic, tactic or operational)?

– What is the domain of this KPI (sales, marketing, production…)?

– What are the dependencies and the influence rate of this KPI with/on other KPI's?

In case there are no decisions to be taken by end users, she/he monitors preconfigured metrics. Such actions fulfill the first phase of decision-making process, which consists out of finding occasion for making a decision. If this occasion shows up (e.g. KPI under or above the defined threshold), the system adapts the user interface to declare the need of decision. The opportunity for making a decision can be triggered in two different ways. The first way is when the stakeholder is reviewing his dashboards and he finds out that a specific KPI reflects a bad situation that should be taken care of. In this case, he will directly select this KPI and enter his decision via the front end. The user should also give the expected result of his decision. In our case he should enter a forecasted value of the KPI and the period when it will meet the newly fixed goal. The second way will be when the system detects a similar situation that has been handled with a previous decision stored in the decision database. The KPIs are monitored and the enhancements are calculated automatically through planed tasks in order to detect "alarming" situations and notify the stakeholder about a situation that requires his attention. Several criteria's can determine a similar situation:

– Trend: If the actual trend of a specific, KPI is the same than its trend in a past situation. For instance, if the sales are dropping for the third consecutive month. The sales values may not be the same, but the trend is similar.

– Periodic events: Based the temporal variation of KPIs, system will detect a horizontal segmentation to define seasonal behavior. For example, if the sales grow every summer.

– Distance to the preset goal: If the distance of a KPI that separate it from the fixed goal is the same as it was in a past period, then the system will consider it as a similar situation.

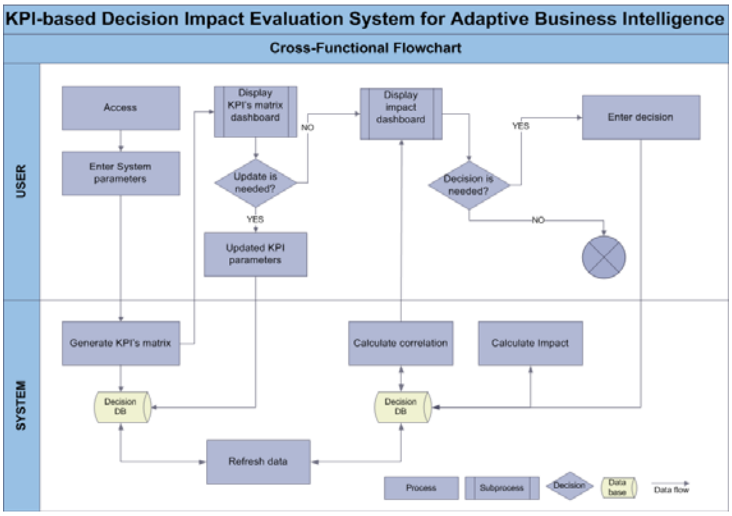

Figure 3. Cross-functional flow chart for decision evaluation system

If one or more of those situations occurs, a dashboard containing the actual value of the KPI, its past value, and the past decisions with their calculated impact will be displayed. The user can choose then the decision with the best impact on global business.

4. Decision evaluation system reference architecture

In this section, the decision evaluation system (DES) reference architecture is explained. Explanations consist out of the components descriptions and interactions between them. The proposed solution assures interactivity between the system and its end users while making decision and it is fully adaptive.

The main outcomes of the proposed concept are aimed at overcoming the shortages in decision-making process of an ABI by making the following:

– Enabling interactions between machines (mainly software) and humans in a decision making process;

– Building relationships between decisions and company's KPIs;

– Tracking, evaluating and recommending decisions.

Figure 4 illustrates the DES reference architecture. The external component data warehouse (DWH) is used to get the KPIs and their values and changes (positive or negative). The primary role of the KPI & Decision Tuner component of the presented DES architecture is to ensure relationships such as: (a) KPI to KPI and (b) KPI to decision. Secondary role of the KPI & Decision Tuner component is to store KPI values in a dedicated storage component such as Decision DB. The main subcomponents of it are the KPI Generator, KPI Classifier, KPI Monitor and KPI Matrix Generator. The communication between the KPI & Decision Tuner and the two databases (the DWH and the Decision DB) is assured through two Data Access Objects (DAOs).

The Decision Engine component enables the interactivity between user and system during the decision making process. Primarily, the component role is to provide the following functionalities: 1) build a relationship between actions and KPIs, 2) simulate decision impact, 3) classify decisions, and 4) generate decision matrix. The Decision Engine component is composed out 6 subcomponents: Decision Generator, Decision/KPI Combiner, Decision Simulator, Decision Matrix Generator, Decision Maker and a DAO.

With no doubt that while conducting a decision-making process some errors may occur. And it is very hard for the individuals to identify and determine these errors since they are presented as truth (Karlsson, 2013). This is one of the reasons why the evaluation of decisions is required. The Decision Evaluator component assures the evaluation of already taken decisions. This evaluation is based on a set of different criteria defined as entry parameters. For now, we won't dive deep into the details of each class of criteria, rather we will explain the main strategy adopted in evaluating the BI decisions. The evaluation criteria are grouped based on their classification aspects. Each criterion is going to be evaluated individually based on the impact of the decision on one or many KPIs. The Impact Monitor subcomponent is responsible for the measurement of the decision impact and gets this information via internal DAO, which communicates with the Decision DB. The average of these criteria will be evaluated on an upper level.

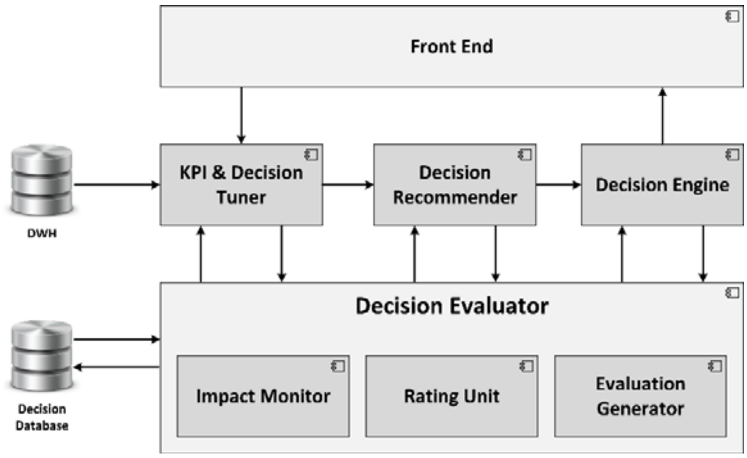

Figure 4. Decision evaluation system reference architecture

To be able to make decisions, the users should know possible choices available to them, as well as they should be informed about their potential success, whether the reputation of a particular choice should be based on its own reputation. According to the work of Etzioni (Etzioni, 1988) “... the term choice should be used to encompass the sorting out of options, whether conscious or unconscious. Deliberate choices are to be referred to as decisions”. The Decision Recommender component gives user all possible decisions (related to her/his profile) to a specific situation. The proposed options are sorted based on their available evaluations. Each choice has its own characteristics. This component adapts the recommended decision to user’s domain (e.g. human resources, sales, marketing, research and development, etc.) and responsibility (e.g. director, adviser, division manager, team lead, employee, etc.). Such limitation is introduced in a sense that it won’t be possible that each user can take all types of decisions. For example, a sale consultant is authorized to decide changing her/his plan while visiting customer, and prioritize important customers on her/his own (e.g. knowledge gained from a customer ranking dashboard).However, the same sale consultant is not authorized to change her/his product portfolio or to start a new marking campaign on her/his own.

5. Implementation

The new layer added to classic ABIS, will allow the users to measure the impact of their taken decisions on global business. It is a self-learning system, it learns as it is being used. To illustrate more clearly the steps to implement this approach, we will use a reel case study that we developed a prototype for. It takes into account all domains managed in the company and calculates the impact of the decisions taken in a specific domain on the overall business. In our case we will study the impact of decisions of HR managers on the global business.

5.1. Sequence diagram

This following sequence diagram describes formally the interaction between the different modules of the system and the users. In our case, we distinguish three user profiles: Decision-maker, Manager, and Administrator. The administrator will setup configurations, such as goals, KPI's list, and domains. The manager will use the system to validate decisions.

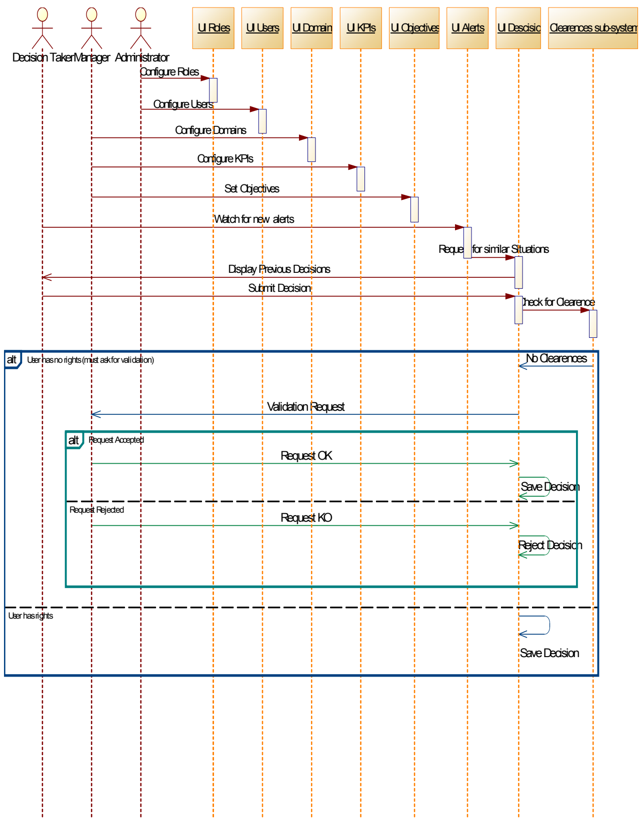

Figure 5. Sequence diagram

5.2. Configuration and settings

The first step is to build the KPI matrix through the prototype front end. It contains the KPI's list with the domain associated with each KPI as shown in the next figure. This KPI classification will allow as calculating the impact of each domain on the other in general.

	HR	Sales	Production
Sales per Rep	☐	☑	☐
Average salary	☑	☐	☐
Rate of Contact	☐	☑	☐
Cycle Time Ratio	☐	☐	☑
Production losses	☐	☐	☑
Cost per hire	☑	☐	☐
Workforce stability	☑	☐	☐
Sales Growth	☐	☑	☐
Rate of Follow Up	☐	☑	☐
Value of work done	☐	☐	☑

Figure 6. Prototype interface for KPI/Domain affectation

The second configuration is related to the business importance/weight of each department in the company. The weight of each domain cannot be determined automatically, it depends on the nature of the activity, the context, and other factors that can affect the importance of each domain on the global business. Thus, an expert should carefully enter this input. The next figure shows the front-end screen that the user can use to enter these parameters.

Domain	Weight
Production	15%
Sales	25%

Figure 7. Prototype interface for Domain weight

The last setting is to set a goal to achieve for every KPI. This configuration can easily be done by entering the information in the decision evaluator knowledge base. The target (goal) should be set for a specific period, and the user can adjust its objectives as the activity runs. The results achieved will be evaluated through a balance dbipolar scale going from very poor to very good. The number of points most commonly used in a balanced scale is 5 points (Dillman *et al.*, 2009).

			Very Poor		Poor		Fair		Good		Very Good	
KPI	Goal	Period	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
Sales per Rep	70%	Q1-2015	-	18%	19%	31%	32%	44%	45%	75%	76%	-
Average salary	35%	Q1-2015	-	25%	26%	35%	36%	50%	51%	80%	81%	-
Rate of Contact	50%	Q1-2015	-	10%	11%	20%	21%	40%	41%	60%	61%	-
Cycle Time Ratio	65%	Q1-2015	-	20%	21%	40%	41%	60%	61%	80%	81%	-
Production losses	66%	Q1-2015	-	15%	16%	31%	32%	44%	45%	65%	66%	-
Cost per hire	40%	Q1-2015	-	18%	19%	31%	32%	44%	45%	75%	76%	-
Workforce stability	81%	Q1-2015	-	20%	21%	40%	41%	60%	61%	80%	81%	-
Sales Growth	60%	Q1-2015	-	30%	31%	45%	46%	50%	52%	75%	76%	-
Rate of Follow Up	40%	Q1-2015	-	25%	26%	35%	36%	50%	51%	80%	81%	-
Value of work done	76%	Q1-2015	-	18%	19%	31%	32%	44%	45%	75%	76%	-

Figure 8. Prototype interface for KPI Goal settings

For every KPI the manager sets a goal to achieve and defines the period during which the goal should be met. This setting will allow the evaluation system to calculate the enhancement or the deterioration of a KPI compared to the expected goal. The goals could be related to the budget or the forecast for financial applications.

5.3. Utilization and calculations

The final step in a classic business intelligence solution is giving useful knowledge to the stakeholder and just trust his intuition or intelligence to make the right decision. The entire system of the adaptive business intelligence was inspired by the decision making model which includes the evaluation step (Simon, 1977). Hence, the user of the new business intelligence system will display the KPI list with their actual values that are displayed in a classical dashboard. If a KPI's value does not fit with the expected result, then we will have an opportunity to make a decision about it and change it for the better.

The user of the new decision evaluation application should enter every decision taken, the KPI that needs to be affected, and the period in which the change will be observed. The decision will be stored with its parameters in the decision database component as a pending decision.

The decision cannot be taken into account before a validation process. The validator can be the user himself, or his hierarchical supervisor. Once the settings are done, the system can now monitor the evolution of the performance of the domain between two dates selected by the user. The impact monitor will give us the enhancements (or deterioration) of the KPI values and by this we will deduce the quality of the decisions made between those dates. In our prototype, two domains are being monitored (Sales and Production).

Sales						
	Was	Is	Goal	Distance was	Distance Is	Difference
Sales Per Rep	23%	52%	70%	-47%	-18%	29%
Rate Of Contact	32%	75%	80%	-48%	-5%	43%
Rate of Follow Up	50%	47%	60%	-10%	-13%	-3%
Sales Growth	45%	53%	20%	125%	133%	8%
Average Enhancement						19%

Figure 9. Prototype interface for KPI/Domain affectation

The enhancement (or deterioration) should be calculated according to a specific goal. Thus, a negative distance shows that the goal is not met yet, and a positive distance shows that the goal is already met or even over-met.

These tables show how to monitor the KPI evolution. In fact, the status "was" is the value of the KPI on the first date and the status "is" reflects the current status of the KPI (after the decision). The average enhancement is calculated as flows:

$$Average\ enhancement = \sum_{i=1}^{nbr(KPI)} Difference \Big/ Nbr(KPI)$$

With:

$$Difference = Distance\ Is - Distance\ Was$$

And:

$$IF\big((Goal - Was) > 0\big)\ THEN\ Distance\ was = 1 + (Goal - Was)$$

$$\text{ELSE}\ Distance\ was = (Goal - Was)$$

And:

$$IF\big((Goal - Is) > 0\big)\ THEN\ Distance\ Is = 1 + (Goal - Is)$$

$$\text{ELSE}\ Distance\ Is = (Goal - Is)$$

We consider that the distance should be negative if the goal is not (or partially) achieved. A distance equals to zero means that the goal is totally achieved (100%). When the value of the KPI exceeds the preset goal then the distance should positive (over 100%). This explains the +1 in the above formula.

After calculating the average enhancement for every domain because of the HR decisions, we should calculate the impact of these decisions of each domain separately. Then calculate the decisions impact on global business. To be able to do this, we will need the weight of the HR domain according to sales, and production. The weight represents the average correlation between KPIs related to HR and KPIs related to the other domains. The objective is to analyze a data set in pairs (bivariate data) and to determine if there is an association (or link) between the two variables.

The correlation coefficient of two variables in a data sample is their covariance divided by the product of their individual standard deviations. It is a normalized measurement of how the two are linearly related. Formally, the sample correlation coefficient is defined by the following formula:

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y}$$

Where:

$$cov = Covariance$$

And:

$$\sigma_X \; is \; the \; standard \; deviation \; of \; X$$

Once the average correlation calculated, we will calculate now the weighted enhancement separately. Then, the global weighted impact of the HR decision as follows:

$$Impact = Correlation \; \times Enhancement$$

Finally, the application will apply the weight initially assigned to the domain by the user. Thus, the impact on global business will be:

$$Impact \; on \; global \; business = \frac{\sum Impact \times Weight}{Nbr(Domains)}$$

At this level, the decision recommender will show a list of the decisions taken in the chosen period from the decision database. And it will assign the calculated impact to those decisions.

6. Survey results

In order to show and motivate the demand for functionalities offered within the proposed ABI architecture, a survey had been conducted. Rosce (1975) proposes that sample sizes larger than 30 and less than 500 are appropriate for most research. The survey consists out of 13 questions that were distributed among companies located in France, Germany, Portugal, Sweden, Algeria and Tunisia with total amount equals to 47 valid responses.

According to Duarte (2010) it is well noted in the literature that managers would ultimately affect a firms' practices. Therefore, middle and top managers from information and communication technology domain are the sample units.

As it is shown in Figure 10, the total amount of respondents coming from Top Management equals to 64,4%, where Middle and Low Management takes 19 and 17% respectively. The most responders came from "Service" sector of market (25 responses), in which the lowest amount came from “Oil & Gas” industry (1 response). On the question of the survey “How can you evaluate the importance of HR KPIs for your organization?” 81% agreed on the importance of KPIs of the human resource within their companies. From them, 19% committed “strong importance” of HR KPIs. On the question of the survey “How can you evaluate the impact of the taken decisions by HR manager and/or staffing manger on your global business?” 53% committed “very high” impact, where 41% agreed on “high” impact and the rest 7% answered as “neutral”.

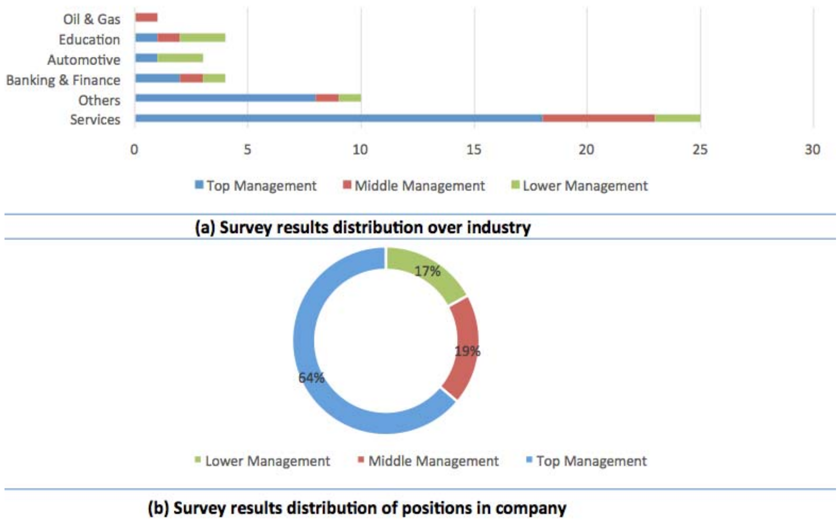

Figure 10. Survey’s results distribution

Figure 11. Importance and impact of HR within company

One hundred per cent of managers who participates in the survey don’t have in their companies a dedicated system, which reflects the relationships between KPIs and their impact to each other. 77% of respondents don’t have a vision about the impact of the taken decision by HR manager and/or staffing manager on their global business. 94% need to have a vision about the impact of the taken decision by HR manager and/or staffing manager on their global business. 23% have a vision about the impact of the taken decisions by HR manager and/or staffing manager on their global business, and 100% of them process manually and provide only estimations. 93% affirmed the impact of HR decisions on their global business (see Figure 11). 100% affirmed the importance of HR KPIs for their business (see Figure 10).

The survey results proves that there is a demands from decision makers in the industry (primary managers on different levels) for a functionality within their BI systems that will increase the awareness of the decision makers about impacts of the performed decisions, relationship between KPIs and possibility to have recommendations for decisions, which will be based on historical decisions.

7. Conclusion

Due to the increasing amounts of data produced internally and externally companies are facing different types of challenges. It is challenging to grasp the main knowledge deeply hidden behind the data and produce decisions based on gathered knowledge, rather than on some "uncertain feelings".

Current work proposes enhancements in the decision-making process within ABI dedicated to the quality improvements of particular decision. The "quality" part comes from past experience and evaluation aspects. The proposed concept consists out of a decision evaluation system within adaptive business intelligence in order to form a connection between decision preparation and decision-making processes and solve issues in decision adaptability in business intelligence.

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