Towards a Context-aware Framework for Assessing and Optimizing Data Quality Projects

Meryam Belhiah, Mohammed Salim Benqatla, Bouchaïb Bounabat and Saïd Achchab
Laboratoire AL QualSADI, ENSIAS, Mohammed V University of Rabat, Rabat, Morocco

Keywords: Data Quality Assessment and Improvement, Data Accuracy, Cost/Benefit Analysis, Business Process Performance.

Abstract: This paper presents an approach to clearly identify the opportunities for increased monetary and non-monetary benefits from improved Data Quality, within an Enterprise Architecture context. The aim is to measure, in a quantitative manner, how key business processes help to execute an organization's strategy, and then to qualify the benefits as well as the complexity of improving data, that are consumed and produced by these processes. These findings will allow to clearly identify data quality improvement projects, based on the latter's benefits to the organization and their costs of implementation. To facilitate the understanding of this approach, a Java EE Web application is developed and presented here.

1 INTRODUCTION

As business processes have become increasingly automated, data quality becomes the limiting and penalizing factor for business processes' performance and overall quality, and thus impacts daily operations, financial and business objectives, downstream analysis for effective decision making, and end-user satisfaction (Wang and Strong, 1996), whether it is a customer, a citizen, an institutional partner or a regulatory authority. The problem of identification and classification of costs inflicted by poor data quality, has been given great attention in literature (Eppler *et al*, 2004), (Haug *et al*, 2011), as well as the definition of approaches to measure Return On Investment (ROI) of data quality initiatives in both research (Otto, 2009) and industrial areas (Gartner, 2011).

Even though the work cited above establishes the overall methodology for measuring the business value of data quality initiatives, it lacks generic and concrete metrics, based on cost/benefit analysis, that can be used by different organizations, in order to facilitate the identification of opportunities for increased benefits, before launching further analysis using additional KPI that are specific to each organization.

The overall goal is not to improve data quality by any means, but to carefully plan data quality initiatives that are cost-effective and that will have the most positive impact. This guidance is particularly crucial for organizations with no or a little experience in data quality projects.

While it is difficult to develop a generic calculation framework to evaluate costs and benefits of data quality projects in money terms, the purpose of this paper is to find a suitable way to assess the positive impact of the improvement of quality of a data object used by a key business process alongside the implementation complexity. This is relevant, because the positive impact and implantation complexity could be transformed to quantitative measures of monetary benefits and costs.

The organization of this paper is addressed as follows: section 2 explains the assessment approach of business processes' overall quality impact on organizations' objectives and results. Factors that summarize the implementation complexity of data quality initiatives are detailed in section 3. Sections 4 and 5 provide an insight into our application. In section 6, the conclusions and future work are summarized.

2 BUSINESS PROCESSES' POSITIVE IMPACT ASSESSMENT

The first part of our approach to track ROI of data

Belhiah M., Benqatla M., Bounabat B. and Achchab S..
Towards a Context-aware Framework for Assessing and Optimizing Data Quality Projects.
DOI: 10.5220/0005557001890194
In *Proceedings of 4th International Conference on Data Management Technologies and Applications* (DATA-2015), pages 189-194
ISBN: 978-989-758-103-8

quality projects consists of understanding how an organization's business/financial objectives and results are linked to key business processes' performance and overall quality. The following steps summarize the process of measuring the positive impact of the performance and overall quality of business processes on the strategy execution of an organization:

1. Identify leading factors that contribute to achieving short-term business/financial objectives of an organization;
2. Configure the importance of these factors according to the specifications of each organization;
3. Measure the impact of key business processes' performance and overall quality on these factors;
4. Order business processes by positive impact.

2.1 Leading Factors That Help Achieving Business/Financial Objectives of an Organization

To understand how business processes' performance and overall quality affect the success of an organization, financial/business objectives and results are detailed as follows:

- Positive impact on daily operations;
- Increasing revenues;
- Increasing productivity;
- Reducing costs;
- Meeting regulatory driven compliance;
- Positive impact on effective decision making;
- Positive impact on downstream analysis.

2.2 Configuration of Importance of the above Factors According to the Specifications of each Organization

Due to organizations' specific aspects and sets of success factors, and in order to provide a generic approach that can be implemented without any adjustment, the second step of our approach introduces the context-aware and configurable weighting coefficients, illustrated in Table 1.

The purpose behind using a weighing coefficient is to allow each organization to express the importance of a success factor, depending of its context and strategy.

To cite few examples where using different weighting coefficients is relevant:

- Public organizations may have more concerns about increasing end-users satisfaction (citizens in this particular case), than increasing revenues;
- Healthcare actors may give more attention to meeting regulatory driven compliance than to the other factors, while still important, owing to the fact that norms and standards are mandatory in the field of healthcare;
- Industrial companies may give the same importance to all the factors above.

Table 1: Configuration canvas for positive impact calculation.

Factor	Values	Rating (R)	Weighting coefficient (I)
Impact on daily operations	true	1	
	false	0	
Impact on short-term business/financial objectives	increasing revenues	0.15	
	increasing productivity	0.15	
	reducing costs	0.15	
	increasing end-user satisfaction	0.15	
	meeting regulatory driven compliance	0.15	
	other	0.15	
Impact on decision making	true	1	
	false	0	
Impact on downstream analysis	true	1	
	false	0	
Is the process cross-functional?	true	1	
	false	0	

2.3 Measurement of the Impact of Key Business Processes' Performance on Overall Quality

Business and IT leaders in charge of data quality initiatives should:

1. List all the key business processes;
2. Configure the importance of each factor by acting on the associated weighting coefficient. The sum of all weighing coefficient must be equal to 100;
3. Answer the questions in the first column of Table 1.

In the case of an organization with many key business processes, the positive impact of each business process will be calculated as follow:

$$\sum_{i=1}^{m}(Ri * Ii)/100 \qquad (1)$$

Where R_i is the rating for the factor "i" and I_i is the weighing coefficient that is associated with the factor "i", that was previously defined by both business and IT leaders. The obtained score ranges between 0 and 5, where "0" refers to "no significant impact" and "5" refers to "high positive impact".

2.4 Order Business Processes by Positive Impact

After iterating over all key business processes and calculating the associated positive impact score, business processes are automatically classified by priority, in order to spot the point of departure to identify opportunities for increased benefits from improved data quality.

As business processes consume and produce data, classifying key business processes by positive impact on an organization's short-term objectives and results, should be followed by the identification of data quality options with the greatest business value at least-cost.

In addition to the positive impact score, other leading indicators may be assessed using the same approach, including: agile transformation of business processes and potential risks that are associated with data quality initiatives. These aspects will be explored in a future work.

Because business processes access data objects in reading and/or writing modes, it is normal that the quality of the data has an impact on the result of business processes' execution and vice-versa.

3 DATA QUALITY PROJECTS ASSESSMENT

While the first part of our approach deals with understanding and assessing how business processes' performance and overall quality positively impact an organization's objectives and results, the second part of our approach focuses on data that are consumed and used by these processes.

Data quality may be defined as "*The degree to which information consistently meets the requirements and expectations of all knowledge workers who require it to perform their processes*" (IAIDQ, 2015), what can be summarized by the expression "*fitness for use*" (Wang *et al*, 1996).

Many researchers tried to establish a classification for data quality dimensions. Below, Pipino *et al* have identified 15 dimensions (Pipino *et al*, 2002):

- Intrinsic: accuracy, believability, reputation and objectivity;
- Contextual: value-added, relevance, completeness, timeliness and appropriate amount;
- Representational and accessibility: understandability, interpretability, concise representation, accessibility, ease of operations, security.

All case studies that aimed at assessing and improving data quality have chosen a subset of data quality dimensions, depending on the objectives of the study (Batini et al, 2012), (Narman et al, 2009), (Aladwani et al, 2002), and (Haug et al, 2011). Measurable metrics were then defined to score each dimension.

We are particularly interested in assessing data quality initiatives that are related to specific dimensions of data quality: accuracy, completeness, availability, validity and restricted access.

The remainder of this paper will focus on the accuracy dimension.

The following steps detail the process of scoring the implementation complexity of data accuracy improvement:

1. Identify leading factors that contribute to the calculation of the implementation complexity of data accuracy improvement ;
2. Configure the importance of these factors according to the specifications of each organization;
3. Measure the positive impact and the implementation complexity ;
4. Prioritize data to improve according to the scores obtained in the previous step.

3.1 Leading Factors that Help Calculating the Implementation Complexity of Data Accuracy Improvement

In this part, the weighting coefficient plays the same role as in the previous part, as it allows taking into consideration the particularities of each organization.

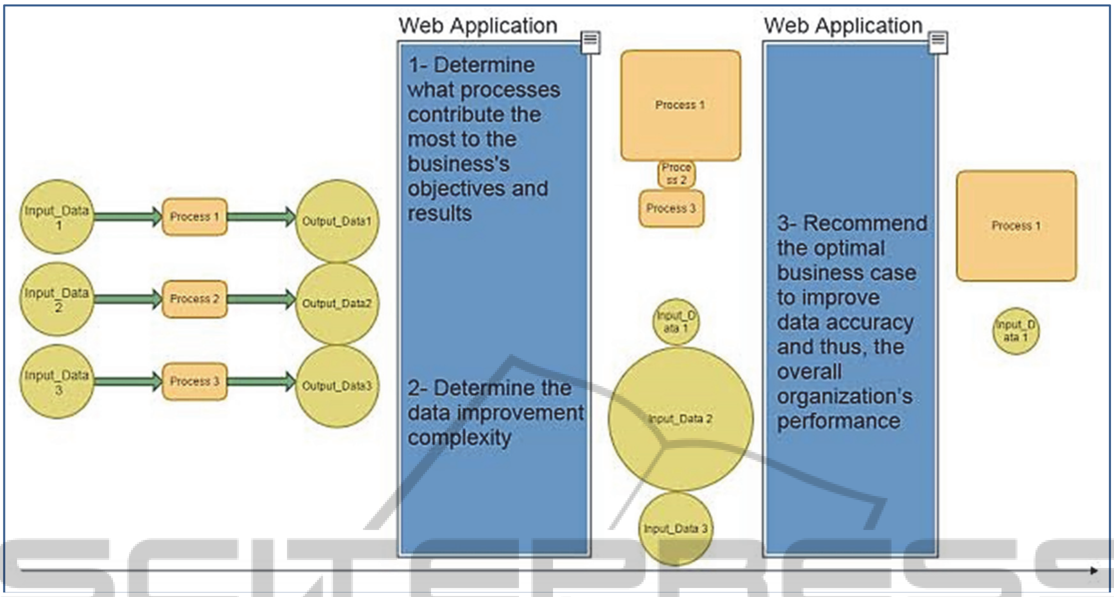


Figure 1: General steps.

Table 2: Configuration canvas.

Factor	Values	Rating (R)	Weighting coefficient (C)
Are there standards to restructure and validate the data?	false	1	
	true	0	
Is there an authentic source of data (repository) that allows to complement or contradict the data?	false	1	
	true	0	
Does the data object have attributes with great weight identification in relation to another data source?	false	1	
	true	0	
Is the data processing:	manual	1	
	semi-automatic	0.5	
	automatic	0.25	
What is the size of the data to process?	very high	1	
	high	0.75	
	medium	0.5	
	low	0.25	

3.2 Measurement of the Implementation Complexity of Data Accuracy Improvement Project

Data profiling activities should allow answering the previous questions (see Table 2). For a given data used by a key business process, the implementation complexity will be calculated as follows:

$$\sum_{i=1}^{m}(Ri * Ci)/100 \qquad (2)$$

Where R_i is the rating for the factor "i" and C_i is the weighing coefficient that is associated with the factor "i", that was defined previously by both business and IT leaders. The obtained score ranges between 0 and 5, here where "0" refers to "minimal complexity" and "5" refers to "severe complexity".

The figure above (see figure 1) depicts our approach.

4 EXPERIMENTAL SETUP

After completing this research, and in order to validate the approach presented in this paper, we are planning to do at least two case studies. We are particularly interested in open-data and e-government fields. Meanwhile, the figures presented

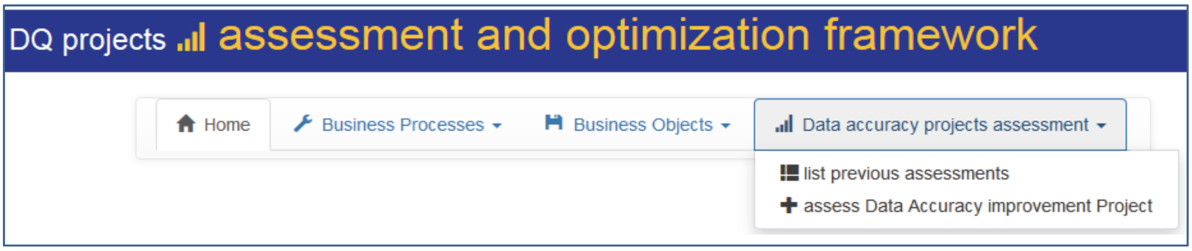
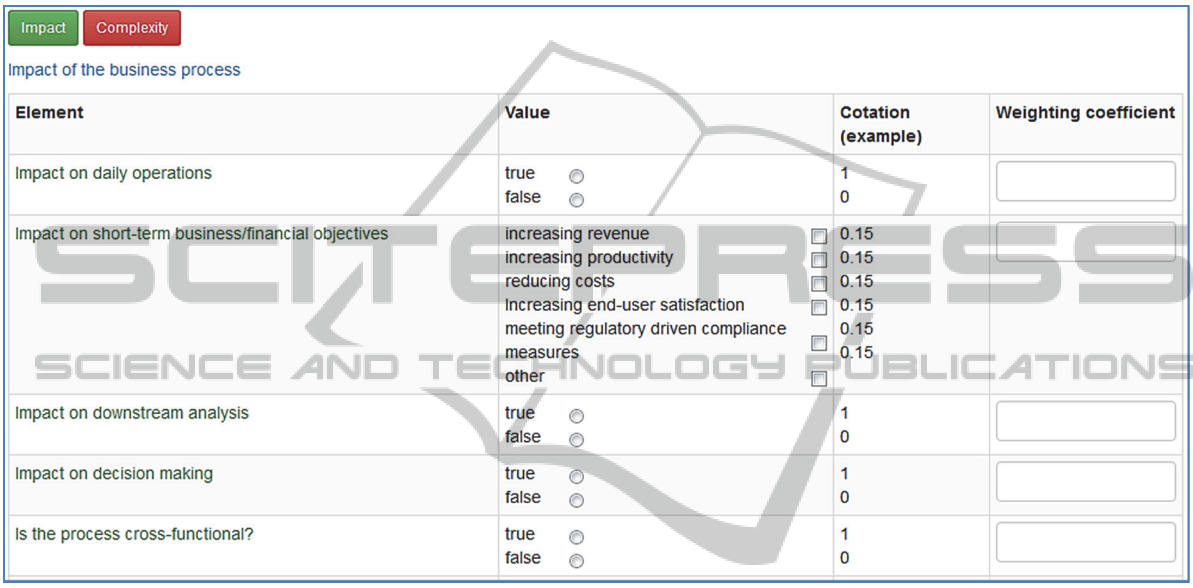


Figure 2: Main menu.

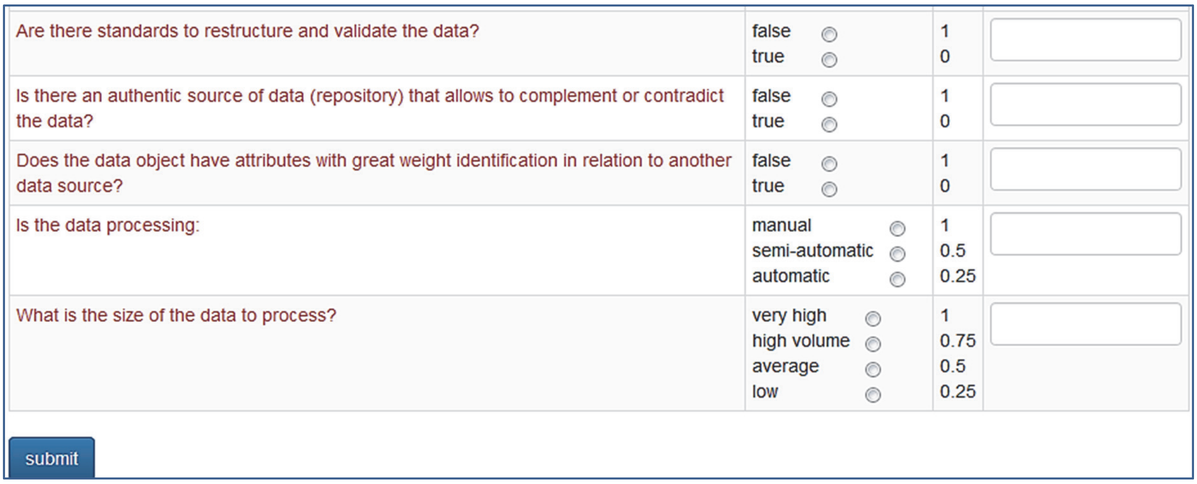


Impact | Complexity

Impact of the business process

Element	Value	Cotation (example)	Weighting coefficient
Impact on daily operations	true false	1 0	
Impact on short-term business/financial objectives	increasing revenue increasing productivity reducing costs Increasing end-user satisfaction meeting regulatory driven compliance measures other	0.15 0.15 0.15 0.15 0.15 0.15	
Impact on downstream analysis	true false	1 0	
Impact on decision making	true false	1 0	
Is the process cross-functional?	true false	1 0	

Figure 3: Calculation framework for positive impact.



Are there standards to restructure and validate the data?	false true	1 0	
Is there an authentic source of data (repository) that allows to complement or contradict the data?	false true	1 0	
Does the data object have attributes with great weight identification in relation to another data source?	false true	1 0	
Is the data processing:	manual semi-automatic automatic	1 0.5 0.25	
What is the size of the data to process?	very high high volume average low	1 0.75 0.5 0.25	

submit

Figure 4: Calculation framework for implementation complexity.

above (see figures 2, 3, and 4) summarize our solution's most important functionalities including:

- Adding a new business process;
- Listing all business processes;
- Adding a new business object (physically implemented by a data object), that is used by a registered business process;
- Listing all business objects;
- Assessing data accuracy improvement projects;
- Listing all previous assessments.

5 RECOMMENDATIONS

We have established two global indicators of positive impact and implementation complexity, to measure the business value of data accuracy improvement projects.

According to the values of these indicators and to the targeted accuracy level (to-be), two business cases may be considered:

- The first one is to improve the processes (reengineering, control, etc.), by enhancing their execution accuracy. This is a short term option that is generally less expensive, but requires change management because it affects the working methods;
- The second one is based on the improvement of data accuracy by determining and analyzing the sources of low quality, such as uncontrolled data acquisition, update problems, etc.

Since the automation of business processes guarantees, in a way, the quality of their execution, actions must be directed towards the improvement of the accuracy of the data used by these processes. Our approach highlights the most cost-effective data accuracy improvement projects.

6 CONCLUSIONS AND FUTURE WORK

The result of the work accomplished thus far shows how to measure in a quantitative manner, the business value of data quality improvement projects, by establishing two global indicators of positive impact and implementation complexity.

In this paper, only the assessment of data accuracy projects was covered. One or more case studies' validation is necessary.

Furthermore, and in order to recommend the optimal business case to improve data accuracy and thus, the overall organization's performance, an optimization algorithm is under development to identify the optimal data accuracy level, taking account of: 1) – the initial data accuracy level (as-is), 2) – the positive impact of the key process that uses the data, 3) – the implementation complexity of data accuracy improvement initiative, and 4) - the targeted data accuracy (to-be).

REFERENCES

Aladwani, A. M., & Palvia, P. C., 2002. Developing and validating an instrument for measuring user-perceived web quality. *Information & management*, 39(6), 467-476.

Batini, C., Comerio, M., & Viscusi, G., 2012. Managing quality of large set of conceptual schemas in public administration: Methods and experiences. In *Model and Data Engineering* (pp. 31-42). Springer Berlin Heidelberg.

Eppler, M., & Helfert, M.,2004. A classification and analysis of data quality costs. In *International Conference on Information Quality.*

Gartner, Oct 2011. Measuring the Business Value of Data Quality. *https://www.data.com/export/sites/data/common/ assets/pdf/DS_Gartner.pdf.*

Haug, A., Zachariassen, F., & Van Liempd, D.,2011. The costs of poor data quality. Journal of Industrial Engineering and Management, 4(2), 168-193.

International Association for Information and Data Quality, 2015. IQ/DQ glossary. *http://iaidq.org/main/glossary.shtml.*

Narman, P., Johnson, P., Ekstedt, M., Chenine, M., & Konig, J., 2009. Enterprise architecture analysis for data accuracy assessments. In *Enterprise Distributed Object Computing Conference*, 2009. EDOC'09. IEEE International (pp. 24-33). IEEE.

Otto, B., Hüner, K. M., & Österle, H. (2009). Identification of Business Oriented Data Quality Metrics. In *ICIQ* (pp. 122-134).

Wang, R. Y., & Strong, D. M.,1996. Beyond accuracy: What data quality means to data consumers. *Journal of management information systems*, 5-33.

Pipino, L. L., Lee, Y. W., & Wang, R. Y., 2002. Data quality assessment. *Communications of the ACM*, 45(4), 211-218.