INFORMATION QUALITY ASSESSMENT: VALIDATING MEASUREMENT DIMENSIONS AND PROCESSES

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Abstract

Over the last two decades information quality has emerged as a critical concern for most organisations. Foremost research provides several approaches to measure information quality and many case studies constantly illustrate the difficulties in assessing information quality. In this paper, we tackle the problem of assessing information quality and we propose a framework to implement information quality assessment in practice. Our framework incorporates two major components: a set of valid measurement dimensions and a measurement process. We have tested the validity, reliability and usefulness of the dimensions and applied the measurement process to an example dataset. In addition, our study demonstrates typical information quality problems in the example dataset and their potential impact to organisations.

Keywords: information quality, information quality dimensions, measurement process, information quality software

1 Introduction

In a broad spectrum of industries, numerous business initiatives have been delayed or even cancelled, citing poor information quality (IQ) as the main reason. The problem of poor IQ has caused various organisational losses, such as losing customers and making incorrect decisions. Case studies of these IQ problems can be found in a plethora of reports, journals and books. Many of the IQ problems are pervasive, costly and even disastrous. For example, more than 60% of 500 medium-size firms were found to suffer from IQ problems (Wand and Wang 1996). It is estimated that an industrial information error rate up to 30% is considered typical and it is often reported that the error rate rises to 75% (Redman 1996). In recognition of the criticality of IQ, organisations have become increasingly aware of its importance (Otto et al. 2009).

The assessment of IQ is a key determinant of IQ management, as one cannot manage IQ without measuring it appropriately (Stvilia et al. 2007). By adapting a general definition of assessment (Gertz et al. 2004), IQ assessment can be defined as the process of assigning numerical or categorical values to IQ dimensions in a given setting. Over the last decade, a number of IQ assessment frameworks have been proposed (e.g. Pipino et al. 2002, Lee et al. 2002, Heinrich et al. 2009, Kaiser et al. 2007); however, in practice, organisations are facing still difficulties when implementing these assessment frameworks (Batini et al. 2009). One major difficulty is to understand and coordinate the quality assessment process for raw data and information products. Typical questions in that context are for example the following: which dimensions are suitable for measuring the quality of raw data in contrast to the quality of information products? How to coordinate the different assessment processes? Examining some of these issues, we conduct a literature review which reveals that most proposed frameworks are too generic to be used for assessment purposes or merely remain at a theoretical stage. Subsequently, in this paper we aim to address the limitations of some IQ frameworks, and develop a practical IQ model on the basis of valid and reliable measurements.

We organize the remainder of the paper as follows: Section 2 provides an overview of related literature on which we can base our IQ assessment framework. Then, Section 3 proposes an assessment framework that consists of a set of measurement dimensions and a measurement process. The framework is tested on a real-world dataset in Section 4. Finally, we conclude our paper by summarizing our research findings and outlining future research works.

2 Related Literature

IQ research is mainly conducted in two research streams: databases and management. The database community follows a technical and data-schema-oriented approach. Most research related to this stream, defines IQ based on data values or instances of data models that are consistent with the specifications in data schemas (e.g. Naumann and Rolker 2000 and Oliveira et al. 2005 follow this definition). Research originating in the management stream is focused on approaches that follow the concepts and principles of Total Quality Management. Researchers regard IQ as information that is fit for use by information consumers (e.g. Wang and Strong 1996 and Bovee et al. 2003 follow this definition). Based on these two research streams, IQ assessments can be differentiated in *objective* IQ assessment and *subjective* IQ assessment (Pipino et al. 2002). Objective IQ assessments are usually based on database integrity rules, which are used by software systems to measure the quality of datasets. In contrast, subjective IQ assessments employ user opinions. Such assessments are typically carried out using surveys or interviews in order to evaluate the quality of information products by information consumers (Caballero et al. 2007, Price et al. 2008).

The advantage of objective IQ assessment is that it allows to process large datasets mainly automatically. With an objective assessment we obtain a single or aggregated assessment result. On the other hand, subjective IQ assessments typically involve user opinions and evaluations on the data samples. The assessment may contain different evaluation results due to the different opinions from different information consumers (Strong et al. 1997). The advantage of subjective IQ assessment is that it allows us to measure IQ along a comprehensive set of IQ dimensions, including dimensions such as believability, reputation and interpretability.

As different assessment approaches focus on different targets, we distinguish between the concepts of data quality and information quality in order to facilitate the practical application of our assessments. This also reflects the well cited differentiation between data and information. Following the same argument, we consider two assessment targets: the raw data stored in databases and the information products created by information systems. While the assessment of raw data measures data in relation to specification (usually based on data integrity rules e.g. Oliveira et al. 2005), the assessment of information products assesses the fitness for use of data.

3 Framework

In this paper we differentiate between raw data and information products; objective (software driven) and subjective (user driven) assessments. We also recognise that certain IQ dimensions can solely be subjectively measures (Price et al. 2008). Based on this observation, in Figure 1, an IQ assessment framework is described. The framework is driven by the idea of "who uses which dimensions to measure what".

- "Who" represents the actor of the data or information assessment. According to the main categories of automatic and human-based task execution, the evaluator can be a person and / or a software program. (Note that although users design the rules and operate the software, we regard software components as independent assessment entities.)
- "What" are the objects that are measured. As discussed above, we consider two measurable objects: (a) raw data stored in the databases and (b) information products are the outcomes from information manufacturing systems.
- "Which" represents the set of IQ dimensions that are used in the assessment.

Based on this idea, our framework includes three layers: the evaluators, assessment dimensions and assessment target.

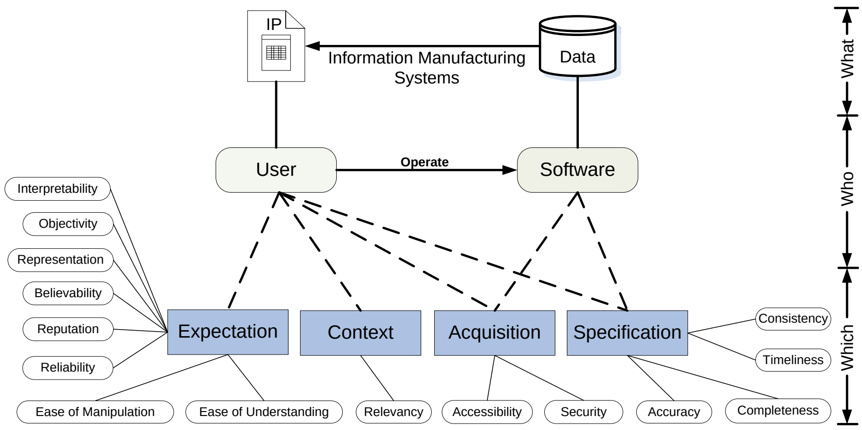

Figure 1. IQ assessment framework.

3.1 Measurement Dimensions

Following prominent IQ frameworks, IQ dimensions can be classified. Therefore, we develop a classification of IQ dimensions and create a survey to validate our classification approach. In contrast to many previous classification schemes that concentrate on intrinsic characteristics of IQ dimensions (e.g. Wang and Strong 1996), we develop a measurement process (see section 3.2) and categorize the dimensions accordingly.

- *Acquisition IQ* represents the extent of accessibility of information. It reflects the characteristics of accessing and retrieving information and measures the extent to which information is available and retrievable. The acquisition dimension includes accessibility measures but also aspects of security and data protection.
- *Context IQ* characterizes the intended use of information and indicates that the use of dimensions relates to a specific context. It measures the extent to which information is relevant and useful. Obviously the user is the main subject involved in context-dependent IQ assessment. Based on the context-related evaluation, users evaluate the relevance of information in a particular context.
- *Specification IQ* measures the extent how information is in accordance with its specification. Typically, specifications are described by data schemas, rules and references. Using these specifications, software programs can be used to assess the specification quality of raw data.
- *Expectation IQ* captures the user-perceived quality of information products in terms of subjective IQ dimensions such as *objectivity* and *believability*. Whereas context IQ measures the objective use of information, expectation IQ measures the subjective element of IQ usages. Obviously, the expectation dimension is subjective and can only be evaluated by humans and thus might result in varying outcomes in different IQ assessments.

Acquisition IQ and context IQ are prerequisites and thus primary measures of IQ as information access is a prerequisite for any further information processing. Context dimensions are a prerequisite for any IQ evaluations because only related information should be further evaluated. In order to validate our classification approach, we create a survey in accordance with the procedure suggested by Churchill (1979). 2 to 5 measuring items are created for each of the 17 dimensions, which results in a total of 56 items. These IQ dimensions and their measuring items are shown in Table 1.

IQ Dimension (17)	**Attributes of Items (56)**
Accessibility	accessible, obtainable, retrievable, available. (4 items)
Security	secure, protected, authorized access. (3 items)
Relevancy	useful, relevant, applicable, helpful. (4 items)
Value-added	beneficial, valuable, add value to operations. (3 items)
Accuracy	correct, accurate, free of error, precise. (4 items)
Completeness	sufficient, complete, comprehensive, include all necessary values, detailed. (5 items)
Timeliness	current, up to date, delivered on time, timely. (4 items)
Consistency	consistent meaning, consistent structure, presented in the same format. (3 items)
Interpretability	interpretable, without inappropriate language and symbol, readable. (3 items)
Objectivity	impartial, unbiased, objective, based on facts. (4 items)
Representation	concise, compact. (2 items)
Reliability	reliable, dependable. (2 items)
Believability	believable, trustworthy, credible. (3 items)
Reputation	from good sources, of good reputation, well referenced. (3 items)
Ease of Manipulation	easy to manipulate, easy to aggregate, easy to combine. (3 items)
Ease of Understanding	easy to understand, easy to comprehend, easy to identify the key point. (3 items)
Appropriate Amount	not too much, not overload, not too little. (3 items)

Table 1. IQ dimensions and measuring items.

In addition, we analyse the importance of common IQ dimensions. The number of supporting previous research works serves as an indicator for selection dimensions. For that purpose, we select the 10 most influential studies in IQ research, which include 8 journal papers and 2 books summarised in Table 2.

	Ballou & Pazer 1985	DeLone & Mclean 1992	Goodhue 1995	Wang & Strong 1996	Wand & Wang 1996	Redman 1996	Pipino et al. 2002	Lee et al. 2002	Bovee et al. 2003	Eppler 2006	Supporting papers
Accessibility		√	√	√		√	√	√	√	√	**8**
Security				√			√	√		√	**4**
Relevancy		√		√	√	√	√	√	√		**7**
Value-added				√			√				**2**
Accuracy	√	√	√	√	√	√	√	√	√	√	**10**
Completeness	√	√	√	√	√	√	√	√	√	√	**10**
Timeliness	√	√	√	√	√	√	√	√	√	√	**10**
Consistency	√	√		√	√	√	√	√	√	√	**9**
Interpretability				√	√	√	√	√	√	√	**7**
Objectivity		√		√	√		√	√			**5**
Representation		√	√	√	√	√	√	√			**7**
Believability				√			√	√			**3**
Reliability		√	√		√						**3**
Reputation				√			√	√			**3**
Ease of Manipulation			√				√	√		√	**4**
Ease of Understanding		√	√	√	√		√	√	√	√	**8**
Appropriate Amount				√		√	√	√			**4**

Table 2. Supporting literature of IQ dimensions.

We obtain a set of the most relevant dimensions by choosing those that are mentioned at least in half of the analysed literature. The selected dimensions include accuracy, completeness, timeliness, consistency, accessibility, ease of understanding, relevancy, interpretability, representation and objectivity. Note that this result also generally conforms to the research findings of Wand and Wang (1996).

In order to confirm the validity of the selected IQ dimensions, we base our approach on existing survey design approaches: (1) Assessing the importance of dimensions (e.g. Wang and Strong 1996, McKinney et al. 2002), and (2) evaluating the given information according to the IQ dimensions (e.g. Lee et al. 2002, Slone 2006). The advantage of the first approach is that users are able to evaluate all the dimensions. However, when using the second approach, some dimensions may not be suitable for evaluating given information. For example, relevancy cannot be evaluated, when no context information is given. Therefore, we design our survey based on the first approach. Similar to McKinney et al. (2002) and Lee et al. (2002), we use an 11-point Likert-type scale. The highest score (10) was labelled as "Extremely important", while 0 was labelled with "Not important at all"; 5 was labelled with "Average". Most questions in the survey had the following structure: "the information that is <Attributes of the Item> is". For example, "the information that is accessible is".

In order to validate the measurement dimensions, three types of validities are tested: face validity, content validity and construct validity.

Face validity evaluates if the proposed items measure the intended use (Anastasi 1988). Usually, it can be tested by reviewing items by untrained judges (Litwin 1995). These untrained individuals are asked to confirm that the measuring items are appropriate for the measurement dimensions. In our study, 10 postgraduate research students in Information Systems review the measuring items for face validity. The respondents confirmed the measure. One respondent suggests that it was difficult for novice users to assign properties to the value-added criteria and as shown in Table 3, only 2 out of 10 papers list this dimension. Therefore we decide to revise our measures and exclude the value-added dimension from our list.

Content validity is used to measure the extent to which the proposed items reflect the specific domain of content (Carmines & Zeller, 1991). Testing content validity requires structured reviews of the instrument's content by experienced professionals. The professionals should possess extensive domain knowledge to be capable to evaluate the measurement approaches. The reviewers evaluate whether the measurement dimensions are complete and correct. For our study, 10 experienced information system researchers review the measurement dimensions. The researchers confirm the measuring approach. One respondent provide comments on the "appropriate amount" dimension. This researcher suggests that if we distinguish the concepts of IQ and information overload, the "appropriate amount" dimension could be combined with the "completeness" dimension. After discussing this with the other researchers, we approve of the comment and drop the "appropriate amount" dimension.

Construct validity comprises two elements: convergent validity and discriminant (also known as divergent) validity. For our research, we build on previous survey instruments, for which construct validity of IQ dimensions is tested. One of the prominent contributions proposed by Wang and Strong (1996) identifies 118 IQ items and uses exploratory factor analysis to derive 15 IQ dimensions. The loading of each dimension was 0.5 or greater (Sample size: 355). Their results support both convergent validity and discriminant validity. Based on Wang and Strong's work, Lee et al. (2002) select 14 IQ dimensions and replace the "value-added" dimension with "ease of operation". Using these dimensions, they examine a correlation matrix of 15 IQ dimensions. Their results demonstrate strong correlations among the different IQ dimensions. According to Slone (2006), discriminant validity was present when constructs display low correlations. Therefore, Lee et al. (2002)' work found that IQ dimensions have weak discriminant validity (Sample size: 261).

Previous research shows inconsistent interpretations of Construct validity. For this reason we decide to confirm Construct Validity of our IQ dimensions by carrying out a further study. In order to purify the proposed IQ dimensions, we carry out a survey in both industry and academia. 316 viable responses were collect from 580 participants, 52% are postgraduate students, 17% are information system researchers and 31% are from industry. The average age of the participants is 31. Based on the collected data, we carry out a confirmatory factor analysis. The factor analysis is summarised in the appendix. The analysis results indicate construct validity of our measurement dimensions.

According to the factor analysis, we extract 9 IQ constructs (loading > 0.6). The dimension interpretability exhibit a cross loading with the ease of understanding dimension. We combine both dimensions into the dimension "understandability". The dimensions reliability, believability and reputation show a cross loading amongst each other. It seems that users consider the information from credible sources or information with a good reputation as reliable and believable. According to Wand and Wang (1996), reliability is found to be the most frequently used in literature and thus we decide to select reliability to represent the three dimensions. The dimensions accuracy, completeness and consistency are also grouped together because users presume that inaccurate information consists of incomplete or inconsistent information. However, due to the common usage of these dimension names, we decide to keep the dimension names and grouped the 3 dimensions to one category. Following Bovee et al. (2003), we name this category as "integrity".

Considering the factors with low loadings, we drop 9 measuring items and the dimension of representation. The remaining items are showing high factor loadings and no significant cross loadings. The outcome of the analysis indicates both Convergent Validity and Discriminant Validity.

Overall, we derive 9 IQ constructs with 41 measuring items. In order to test their reliability, Cronbach alphas were computed. This evaluates how well the dimensions captured the variance of the measuring items. In Table 4, the Cronbach alpha values are listed and the derived constructs are categorized by our classification.

Category	Construct	Number of Items	Cronbach Alpha
Acquisition	Accessibility	4	0.91
	Security	3	0.88
Context	Relevancy	4	0.81
Specification	Integrity	10	0.79
	Timeliness	3	0.92
Expectation	Understandability	5	0.86
	Reliability	6	0.81
	Ease of Manipulation	3	0.83
	Objectivity	4	0.77

Table 3. Results of Cronbach Alpha.

As shown in Table 3, the Cronbach alpha values of the IQ construct range from 0.77 to 0.92. According to the acceptable rate of 0.7 (Nunnally, 1967), the results support Convergent Validity and indicated measures of each dimension with high reliability. That means the dimensions in the construct column are validated and can be directly used in future assessment approach.

3.2 Measurement Process

Using the measurement classification above, we develop measurement processes for assessing the quality of data and information. As discussed above, we differentiate between the assessment of raw data and information products.

3.2.1 Measurement of Raw Data

Raw data can be assessed by an automatic procedure. Since the context and expectation IQ dimensions are not applicable for assessing raw data, we focus in this initial assessment step on the categories of acquisition and specification. The assessment process for raw data is organized in 5 steps (Figure 2). The IQ dimensions related to acquisition are first used and then subsequently IQ dimensions in the category of specification are assessed.

Figure 2. Process to assess the quality of raw data.

The standard values or value ranges for each of the fields in a database are specified. Then we identify those IQ problems that violate the specifications and relate these IQ problems to IQ dimensions. If an IQ problem is connected to multiple IQ dimensions, it may cause dependencies among these IQ dimensions. In order to reduce the dependency among IQ dimensions, we link each problem to only one IQ dimension but one IQ dimension can be connected to different IQ problems. Dimensions that are not linked to any IQ problems are dropped in the assessment. Finally, an IQ report is generated for IQ analysis and improvement.

3.2.2 Measurement of Information Products

In the following, we propose a measurement process for assessing the quality of information products (Figure 3). It is primarily a human-based procedure and is first assessed by IQ dimensions of acquisition category. We then assess the information products with the help of Context IQ dimensions. If the IQ assessments are context related, evaluators firstly need to understand the intended use of the information and then information products can be identified. The evaluators also need to precisely understand the definitions and subscales of each IQ dimension. Then, evaluators can use these IQ dimensions to evaluate whether given information products are fit for the intended use. Finally, each evaluator will generate a report. The Specification IQ and Expectation IQ dimensions are used to assess the information products. The assessment is complete when the information products are completely inaccessible or accessible but irrelevant.

Figure 3. Process to assess the quality of information products.

In order to validate and demonstrate our measurement process, we have applied the method in a practical oriented scenario which is described in the following.

4 Application

We apply our measurement dimensions and process to a real world dataset, the Samsclub dataset, provided by the Walton College Teradata system. The dataset contains retail sales information gathered from sales at Sam's Club stores, a division of Wal-Mart Stores Inc. The database consists of 6 tables and 57 attributes. We focus on the table of member_index and store_visits.

4.1 Measurement of Raw Data in the Case Study

To illustrate the use of the proposed measurement dimensions and process, we select the table member_index as the measuring object and assess the quality of the raw data. We summarize the procedure of assessing this dataset in Table 4. In the example dataset we assume that the raw data are both accessible and secure.

<table>
<tr><th rowspan="7">Make Specifications</th><th colspan="2">Field</th><th colspan="3">Specification (Possible values)</th></tr>
<tr><td colspan="2">BUS_CR_TYP_STAT_CD</td><td colspan="3">1-5,7,9</td></tr>
<tr><td colspan="2">CMPLMNTRY_CARD_CNT</td><td colspan="3">0,1,2</td></tr>
<tr><td colspan="2">ELITE_STAT_CODE</td><td colspan="3">0,2,3,4</td></tr>
<tr><td colspan="2">MEMBER_STATUS_CD</td><td colspan="3">A,D,E,T</td></tr>
<tr><td colspan="2">MEMBER_TYPE</td><td colspan="3">1,A,E,G,V,W,X</td></tr>
<tr><td colspan="2">QUALIFY_ORG_CODE</td><td colspan="3">null, 0015-3001</td></tr>
<tr><th>Identify IQ Problems</th><td colspan="5">P1. The data value is null except in the field QUALIFY_ORG_CODE.
P2. Figures are expressed in English (for example, describing 0 as zero).
P3. Spelling errors and case sensitivity.
P4. Except for the above situations, data values do not conform to the specification.</td></tr>
<tr><th rowspan="5">Link IQ Problems To IQ Dimensions</th><td></td><td>Accuracy</td><td>Completeness</td><td>Consistency</td><td>Timeliness</td></tr>
<tr><td>P1</td><td></td><td>√</td><td></td><td></td></tr>
<tr><td>P2</td><td></td><td></td><td>√</td><td></td></tr>
<tr><td>P3</td><td>√</td><td></td><td></td><td></td></tr>
<tr><td>P4</td><td>√</td><td></td><td></td><td></td></tr>
<tr><th>Assess Quality of Raw Data</th><td colspan="5">Automatic Procedure</td></tr>
<tr><th rowspan="6">Generate Report</th><td colspan="5">Database: UA_SAMSCLUB, Table: MEMBER_INDEX, Records: 5668375</td></tr>
<tr><td colspan="2"></td><td>Accuracy</td><td>Completeness</td><td>Consistency</td></tr>
<tr><td colspan="2">BUS_CR_TYP_STAT_CD</td><td>99.983% (933)</td><td>99.999% (17)</td><td>100%</td></tr>
<tr><td colspan="2">CMPLMNTRY_CARD_CNT</td><td>99.999% (19)</td><td>100%</td><td>100%</td></tr>
<tr><td colspan="2">ELITE_STAT_CODE</td><td>99.806% (10954)</td><td>100%</td><td>100%</td></tr>
<tr><td colspan="2">MEMBER_STATUS_CD</td><td>100%</td><td>100%</td><td>100%</td></tr>
</table>

	MEMBER_TYPE	99.833% (9418)	100%	100%
	QUALIFY_ORG_CODE	98.263% (98424)	100%	100%

Table 4. Assessing quality of raw data.

For this case scenario we rely on specifications provided by the database system. Four IQ problems are identified and linked to different IQ dimensions. The aspect of timeliness was dropped because no IQ problem was connected to this dimension. After the automatic assessment procedure, a simple IQ report was generated. This report state that 5.668.375 records were assessed, of which 119.765 contained IQ problems. As Sam's Club store was a membership-based store, information about its members was obviously crucial for their business. The results have shown that IQ deficiencies exist in the database.

4.2 Measurement of Information Products in the Case Study

In order to assess the quality of information products, we develop an online survey to implement the evaluation procedure. The survey consist of three major parts: The first part was designed to provide introductory information. This information includes a description of the scenario, the procedure of identifying information products and definitions and subscales of the IQ dimensions. The second part contains the evaluating tool in which users can evaluate the quality of the information products by adjusting slider bars for each IQ dimension. The slide bar was scaled from 0% ("not at all") to 100% ("completely"). If an IQ dimension was not applicable for the current evaluation, users could label this dimension as “N/A”. The third part was designed to collect contextual information (e.g. intended use), demographic information and the evaluation results. Based on the collected information, the online survey was used to generate an assessment report for each user.

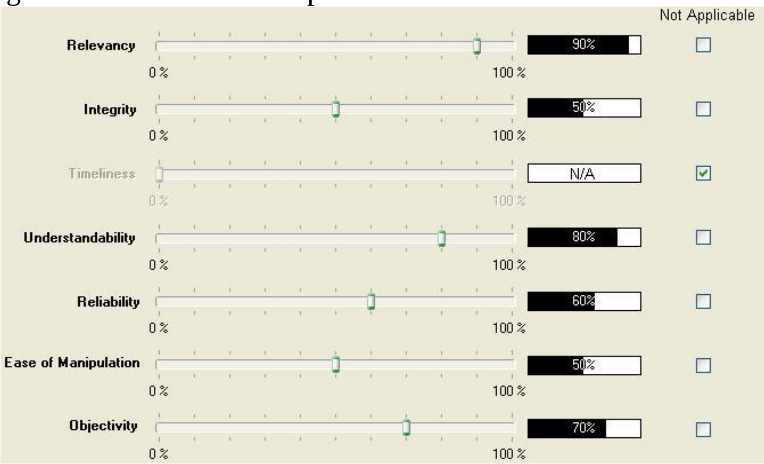

Figure 5. Online survey for assessing information products.

30 postgraduate students participate in the evaluation. These students were registered users of the Teradata system and all of them have used the system prior to the study. We use a customer service scenario in which we show an inventory of information products manufactured from the Samsclub dataset to the users. The IQ dimensions and the intended use of these information products were explained to the users. Subsequently they were asked to evaluate the information products along the defined IQ dimensions. As we consider that the information products are accessible and secure, accessibility and security were not used in the evaluation.

When evaluating the results, it can be seen that information integrity was rated very low: this dimension has the lowest mean value and at the same time 90% of the users gave their lowest evaluation value to this dimension. We could also observe that users were generally not satisfied with accuracy, completeness and consistency of the information products. 40% of the users assigned *not applicable* to the dimension *ease of manipulation*. Understandability and reliability showed the greatest variability. This indicates that users may have different interpretations of understandability and reliability of information products.

5 Summary and concluding remarks

This study proposes a framework to organize the IQ assessment in organisations. This framework consists of two major components: a set of valid measurement dimensions and a measurement process. The 17 dimensions commonly used in literature are tested by confirmatory factor analysis and Cronbach alpha analysis. These dimensions are tailored to a set of 9 dimensions. The analysis of our results supports a strong reliability and validity of the measuring dimensions. Since we differentiate the measuring objects into raw data stored in database and information products delivered to users, two assessment processes are accordingly developed. Our results show that IQ problems are prevalent in a real-world database. When these deficient data are manufactured into information products for business decisions, it can result in incorrect decisions and lower competitiveness. Therefore our exemplary results indicate the importance of raising the awareness of IQ management.

Our findings demonstrate that IQ is a complex and multi-dimensional phenomenon, which has yet not been fully understood. This causes challenges to measure IQ and may explain why current frameworks have their limitations. Our findings help to confirm and clarify the dependencies among the dimensions. Also our work can help the organisation to appropriately use subjective and objective assessment methods since we differentiate raw data and information products in information manufacturing systems

Although our framework and results shows benefits, it also has some limitations. First, the assessment of raw data is limited to relational databases. In the future, we plan to refine assessment process and implement it into a tool. Second, the assessment of information products is designed in a customer service scenario. As this is a simplified experimental setting, it may ignore other influential factors. Therefore as a future work, we will implement this assessment in a real-world business scenario.

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Appendix

Constructs	Items	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Factor 9
Accessibility (4)	Accessible		0.726							
	Obtainable		0.601							
	Retrievable		0.751							
	Available		0.692							
Security (3)	Secure							0.818		
	Protected							0.787		
	Authorized							0.771		

Relevancy (4)	Useful	0.723						
	Relevant	0.686						
	Applicable	0.643						
	Helpful	0.718						
Ease of Understanding Interpretability (5)	Easy to understand				0.706			
	Easy to comprehend				0.816			
	Easy to identify points				0.615			
	Interpretable				0.693			
	Readable				0.627			
Ease of Manipulation (3)	Easy to manipulate		0.605					
	Easy to aggregate		0.722					
	Easy to combine		0.675					
Objectivity (4)	Impartial						0.782	
	Unbiased						0.693	
	Objective						0.793	
	Based on facts						0.828	
Reliability Believability Reputation (6)	Reliable			0.696				
	Believable			0.627				
	Trustworthy			0.788				
	Credible			0.628				
	From good sources			0.787				
	Good reputation			0.621				
Accuracy Completeness Consistency (9)	Correct					0.735		
	Accurate					0.797		
	Free of error					0.691		
	Precise					0.710		
	Sufficient					0.635		
	Complete					0.603		
	Comprehensive					0.612		
	Consistent meaning					0.657		
	Consistent structure					0.688		
Timeliness (3)	Current							0.870
	Up to date							0.898
	Timely							0.795