# DATA QUALITY ASSESSMENT IN CREDIT RISK MANAGEMENT BY A CUSTOMIZED TOTAL DATA QUALITY MANAGEMENT APPROACH

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# ABSTRACT

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As the size and complexity of financial institutions, more specifically banks, grow, the amount of data that information systems (IS) of such institutions need to handle also increases. This leads to the emergence of a variety of data quality (DQ) problems. Due to the possible economic losses due to such DQ issues, banks need to assure quality of their data via data quality assessment (DQA) techniques. As DQ related problems diversify and get complicated, the requirement for contemporary data quality assessment methods becomes more and more evident. Total Data Quality Management (TDQM) program is one of the approaches where data quality assessment of banking data is performed since the phases of the program, i.e. definition, measurement, analysis and improvement are well suited for identification of DQ issues. This study presents a customized approach to TDQM for data quality assessment in credit risk management. The study grounds the selection of DQ dimensions for credit risk on identification of data taxonomies for credit risk in accordance with the Basel Accords. Identification of data taxonomies from an IS viewpoint results in determination of data entities and attributes, which enabled the development of DQ metrics based on the DQ dimension selected in the definition phase. DQ metrics are transformed into quality performance indicators in order to assess quality of credit risk data by means of DQA methods in the measurement phase. Analysis of the results of DQA reveals the underlying causes of poor DQ performance in the analysis phase of TDQM. Identification of DQ problems and their major causes is followed by suggestion of appropriate improvement techniques based on the size, complexity and criticality of the problems in the context of credit risk management. TDQM approach customized for credit risk context in this study is implemented for a real bank case. Results of the implementation indicate the significance of and requirement for implementation of such methods sector-wide in order to manage the risks related to poor DQ. Moreover, a survey addressing banks to evaluate validity, applicability and acceptance of the approach as well as their own ongoing data governance activities has been carried out with the participation of senior risk managers. Findings of the survey reveal that the banks surveyed have found the approach to be considerably satisfactory in addressing data quality issues in credit risk management.

**Keywords:** Data Quality Assessment, Total Data Quality Management, Information Systems, Credit Risk Management, Banking

# ÖZ

## KREDİ RİSKİ YÖNETİMİNDE ÖZELLEŞTİRİLMİŞ TOPLAM VERİ KALİTESİ YÖNETİMİ YAKLAŞIMI İLE VERİ KALİTESİNİN DEĞERLENDİRİLMESİ

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Finansal kuruluşların, daha özelde bankaların, büyüklüğü ve karmaşıklığı arttıkça, bu kuruluşların bilgi sistemlerinin (BS) üstesinden gelmesi gereken veri miktarı da artmaktadır. Bu durum çeşitli veri kalitesi (VK) problemlerinin ortaya çıkmasına neden olmaktadır. Bu gibi VK problemlerinden kaynaklanan olası ekonomik kayıplarından dolayı; bankların verilerinin kalitelerini, veri kalitesi değerlendirme (VKD) teknikleriyle sağlaması gerekmektedir. VK ile ilgili problemler farklılaştıkça ve karmaşıklaştıkça güncel veri kalitesi yöntemlerine olan ihtiyaç gittikçe daha belirgin hale gelmektedir. Toplam Veri Kalitesi Yönetimi (TVKY) programı, bu programın tanımlama, ölçme, analiz ve iyileştirme aşamalarının VK problemlerini tespit etmeye elverişli olmasından ötürü bankacılık verilerinin kalitesinin değerlendirilmesinde kullanılan yaklaşımlardan biridir. Bu çalışma kredi riski yönetiminde veri kalitesinin değerlendirilmesi için TVKY'ye ilişkin özelleştirilmiş bir yaklaşım sunmaktadır. Söz konusu çalışma kredi riskine ilişkin VK boyutlarının seçimini, Basel sermaye uzlaşısına uygun bir şekilde, kredi riskine ilişkin veri sınıflarının tanımlanmasına dayandırmaktadır. Veri sınıflarının BS bakış açısıyla tanımlanması, tanımlama aşamasında seçilen VK boyutlarına dayanan VK ölçütlerinin geliştirilmesini sağlayan veri varlıklarının ve bu varlıklarının belirlenmesiyle sonuçlanmaktadır. VK ölçütleri, ölçme aşamasında, VKD yöntemleriyle kredi riski verilerinin kalitesini değerlendirmek amacıyla kalite performans göstergelerine dönüştürülmektedir. TVKY'nin analiz aşamasında VKD sonuçlarının analizi yetersiz VK performansının temel sebeplerini göstermektedir. VK problemlerinin ve bunların temel sebeplerinin tespit edilmesi, kredi riski yönetimi çerçevesinde bu problemlerin büyüklüğü, karmaşıklığı ve kritikliğine göre iyileştirme tekniklerinin önerilmesine öncülük etmektedir. Bu çalışmada kredi riski çerçevesine uygun olarak özelleştirilen TVKY yaklaşımı, gerçek bir banka örneği üzerinde uygulanmaktadır. Uygulama sonuçları, bu tür yöntemlerin yetersiz VK'ya ilişkin riskleri yönetmek amacıyla sektör genelinde uygulanmasının önemini ve gerekliliğini göstermektedir. Ayrıca, bankaların kıdemli risk yöneticilerinin katılımıyla; bankaların hem önerilen yaklaşımın geçerliliğini, uygulanabilirliğini ve kabulünü hem de kendi veri yönetişim faaliyetlerinin değerlendirmesini ele alan bir anket uygulanmıştır. Anket sonuçları, ankete katılan bankaların söz konusu yaklaşımı bankalar bünyesinde kredi risk yönetimindeki veri kalitesine ilişkin meseleleri ele almakta önemli ölçüde yeterli bulduğunu göstermektedir.

**Anahtar Kelimeler:** Veri Kalitesi Değerlendirmesi, Toplam Veri Kalitesi Yönetimi, Bilgi Sistemleri, Kredi Riski Yönetimi, Bankacılık

*To my wonderful parents*

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# ABBREVIATIONS AND ACRONYMS

| | |
|---|---|
| **BCBS** | Basel Committee on Banking Supervision |
| **BB** | Banking Book |
| **BIS** | Bank for International Settlements |
| **BPMN** | Business Process Modelling Notation |
| **BRSA** | Banking Regulation and Supervision Authority (BDDK in Turkish) |
| **CAR** | Capital Adequacy Ratio |
| **CCF** | Credit Conversion Factor |
| **CQPI** | Composite Quality Performance Indicator |
| **CRA** | Credit Rating Agency |
| **CRM** | Credit Risk Mitigation |
| **CRMB** | Credit Risk Management for Banking |
| **DBMS** | Database Management System |
| **DQ** | Data Quality |
| **DQA** | Data Quality Assessment |
| **ETL** | Extract, Transform and Load |
| **FK** | Foreign Key |
| **ID** | Identity |
| **IRB** | Internal Rating Based |
| **IS** | Information Systems |
| **ISIN** | International Securities Identification Number |
| **IT** | Information Technology |
| **KQPI** | Key Quality Performance Indicator |
| **LGD** | Loss Given Default |
| **MIS** | Management Information Systems |
| **PD** | Probability of Default |

|  |  |
|---|---|
| **PK** | Primary Key |
| **RWA** | Risk-Weighted Asset |
| **SA** | Standard Approach |
| **SME** | Small and Medium sized Enterprises |
| **SQL** | Structured Query Language |
| **TB** | Trading Book |
| **TDQM** | Total Data Quality Management |

# CHAPTER 1

# INTRODUCTION

Acquisition, processing and use of data play an essential role for all business organizations in maintaining their business activities during their life cycle. As regards the financial systems and their stakeholders such as financial institutions, investors, customers, related government bodies and regulators; the criticality and significance of data and its quality which can be measured in different dimensions is indispensably high in terms of maintaining a safe and sound financial system. Banks or credit institutions constitute a significant portion of any macro-level financial system. Information systems (IS) of those institutions are expected to meet requirements related to quality of data. As size and complexity of financial data processed in databases of those institutions increase, the need for assessment of data quality (DQ) becomes more crucial. Data quality assessment (DQA) techniques and methods increase and diversify as the complexity and size of data flowing through information systems of banks reach the point where quality assurance becomes difficult and hardly controllable. Moges et al. (2013) highlight that the risk of poor DQ increases as a result of collection and maintenance of larger and more complex information resources. Yin et al. (2014) put emphasis on the implications of DQ related problems on banks in terms of direct economic impact, and influence on strategic decisions of the banks.

International standards on regulatory capital measurement of banks set and imposed by the Basel Committee on Banking Supervision[1] (BCBS) is evolving since the first framework referred as Basel I. Implementation of next frameworks, Basel II and Basel III, requires producing and dealing with a huge amount of data related to banks' exposures. For sound risk management, banks should manage their credit risk data properly and ensure their quality. Therefore, data quality management and data governance under appropriate and well-established management information systems (MIS) have become crucial aspects of risk management practices. Data quality management and assessment play an important role for a sound and safe financial system in which financial risks are controlled and mitigated.

Emphasizing the significance of data quality management and assessment for risk management activities of banks, Basel Committee on Banking Supervision (BCBS) has published a document that introduces "principles for effective risk data

[1] BCBS is the primary global standard-setter for the prudential regulation of banks and provides a forum for cooperation on banking supervisory matters. Its mandate is to strengthen the regulation, supervision and practices of banks worldwide with the purpose of enhancing financial stability. Turkey is a member of the Committee. (https://www.bis.org/bcbs/).

aggregation and risk reporting”. The document suggests numerous principles to improve risk data aggregation capabilities of banks and their risk reporting practices. The principles cover four main issues. These are data governance and infrastructure, data aggregation and reporting and review of first three issues by the supervisory authority.

## 1.1 Problem Statement and Motivation

Accurate calculation and allocation of regulatory and economic capital require banks to accumulate and utilize high quality of risk data. Low quality data may cause uncertainties in accurate quantification and measurement of banking risks involved. Low quality data may stem from numerous reasons. It may be due to unhealthy process of data accumulation as well as structural problems in data aggregation capabilities of the bank. Such problems may cause missing or incorrect data values and inconsistencies among different datasets. Considering the amount and type of data accumulated, utilized and stored in databases of banks, such data related anomalies can lead to ambiguity in materialization of banking risks, thus, underestimation or overestimation of these risks and capital to be held. Therefore, banks must define clear data taxonomies consistently with the general regulation schemas of the Basel Accords and in accordance with overall information technology (IT) requirements. In addition to structural requirements of data itself, referential integrity among data tables and datasets is critical to sound risk management practices. Definition and measurement of quality of risk data depend on the content of data taxonomies. Data quality requirements which are expressed by quality dimensions or attributes may differ from one data type to another. Therefore, DQ dimensions of each data type in concern for DQ assessment should be defined accordingly. Each dimension implies development of its own DQ metrics. DQ metrics are key to assess DQ of risk data. Assessment of performance of DQ metrics paves the way to detect underlying causes of low data quality. Detection of problems related to data quality may lead to correction in the existing information system or employment of a new one instead of the outdated one.

There are valuable studies attempting to assess DQ of financial risk data. These studies are outlined in Sections 2.2 and 2.5. However, these studies do not go beyond the definition of data quality dimensions for financial data. This reveals the clear need for thorough assessment of data quality of financial data. Increasing sophistication in measurement and evaluation of banking risk data, if not controlled, gives rise to challenges threatening ensuring data quality such as discrepancies among multiple data sources that are used for common operations and increasing manual workarounds. Application of suitable DQA methods is important for maintaining sound risk management system as its findings or inferences are critical for improvement activities. Thus, they ultimately contribute to building integrated IT systems containing well-defined data taxonomies and centralized data repositories in which reconciliation of different data sources is ensured.

## 1.2 Scope of Study

Financial data owned and used by financial institutions consist of various data types. The scope of the present study only covers credit risk data used by credit institutions, i.e. banks. The present study will focus on data quality assessment of credit risk data from an IS viewpoint since it constitutes a major portion of the overall risk exposure. A Total Data Quality Management (TDQM) approach is adopted since its phases are suitable for credit risk context. Phases of TDQM are followed in the study to define DQ dimensions and metrics to be used in DQ assessment. TDQM consists of definition, measurement, analysis and improvement phases. The study covers all four phases to adapt credit risk data to TDQM. The definition and the measurement phases of the proposed approach are deeply elaborated in the present study. The analysis and the improvement phases are also paid considerable effort in the study.

## 1.3 Thesis Outline

The study will first consider the data quality concept and its dimensions by reviewing the literature and data quality assessment methods studied in the literature. Then, the subjects of what DQ assessment means to banking risk data and how it can serve the assessment of the DQ of risk data will be explored. Chapter 3 will examine the taxonomy of overall risk data by focusing on credit risk, define DQ dimensions for credit risk data by benefiting from previous studies, and develop metrics for each DQ dimension defined. In fact, definition of these metrics constitutes the fundamental contribution of the present study. Chapter 4 discusses the implementation of the IS components that will support TDQM in the specific case of the Turkish supervisory authority, Banking Regulation and Supervision Agency (BRSA, BDDK in Turkish). Chapter 5 presents the findings of a survey carried out on a number of banks in order to get feedback on validity, applicability and acceptance of the proposed approach. Chapter 6 discusses on the findings of the study, contribution of the study to the field of DQA in the context of credit risk management, conclusion of the study, limitations for the study, and suggestions for future research.

# CHAPTER 2

# LITERATURE REVİEW

This chapter reviews the literature review on the data quality concept, data quality dimensions and data quality assessment. It also refers to the studies addressing the necessity for DQ assessment of banking risk data from an IS viewpoint in addition to justification and motivation of such assessment by the banking regulations and frameworks, i.e. Basel frameworks.

## 2.1 Data Quality and Data Quality Dimensions

### 2.1.1 Data Quality

It is hard to define data quality since data itself may be quantitative or qualitative, and its value may be derived according to different fields or disciplines. Data quality can be defined and understood differently in terms of specific task or context. Therefore, there is no clear-cut definition of data quality. Due to dependence on context or its use, data quality is often referred as 'fitness for use' in the quality literature. Wang and Strong (1996) giving reference to this general definition, define data quality as "data that are fit for use by data consumers". Juran (1999), an authority in the field of quality management, suggests that data are of high quality if they are fit for their intended uses in operations, decision making and planning. Alternatively, the data can be regarded as of high quality if it correctly represents the real world construct to which they refer. Kahn and Strong (1998), and Huang et al. (1998) also refer to the satisfaction of users' needs or expectations while defining data quality. Based on those views, high or poor quality of data can be interpreted differently according to purpose of use of data. That would imply that data may be viewed as having poor quality by a party while it can have high quality for another party based on their intended use.

As data quality concept can be interpreted differently in different disciplines, its definition, measurement and assessment can be based on different dimensions. Such multi-dimensional nature of data quality is emphasized by Pipino et al. (2002), Redman (1996), Wand and Wang (1996), and Wang and Strong (1996).

### 2.1.2 Data Quality Dimensions

Quality of data should be measured along with various dimensions and attributes of data. Determination of these dimensions is key for defining metrics for data quality and measuring it accordingly. Data quality can be perceived differently in different contexts. In Section 2.1.1 it is pointed out that perception data quality depends on the purpose of users of data within certain context. Data users or “data customers” are those who need data to process according to a specific purpose. Implying the nature of data quality of dependence on the context, Wang and Strong (1996) define data quality dimension as set of attributes that represent a single aspect or construct of data quality.

Determination of data quality dimensions depends on the purpose of use of the data. Therefore, there is no definite set of dimensions. Accordingly, it should be determined on task basis and the nature of data quality problem. Due to that nature, there are considerable differences in the definition of data quality dimensions. These differences are revealed in various data quality related studies. Different data quality assessment methods use different sets of data quality dimensions. There are also discrepancies in the exact meaning of same dimensions. Overwhelming DQ dimensions explored or mentioned in numerous studies are *accuracy, completeness*, *consistency* and *timeliness*.

Wang and Strong (1996) define *accuracy* as “the extent to which data are correct, reliable and certified free of error”. Redman (1996) instantiates the definition of accuracy as the measure of proximity of data value x to another value x’ whose correctness is assumed. Dejaeger et al. (2010) give definition of accuracy similar to that of Redman as the degree of correct representation of real-life values in terms of not only syntactic accuracy but also semantic accuracy. Syntactic accuracy is much more related to organization and order of data while semantic accuracy is much more related to what data means or refers. Batini et al. (2009) emphasizes that only syntactic accuracy is considered in data quality assessment methods. Ballou and Pazer (1985) also view accuracy as correspondence of data to real-world values.

Dejaeger et al. (2010) refer to *consistency* as fulfillment of constraints for each observation. The study highlights two aspects of this dimension which are intra-relational consistency and inter-relational consistency. The first aspect is related to consistency of all records within a data set while the latter one is related to consistency of rules applied to records in one data set with another data set. Batini et al. (2009) refer the consistency as the no violation of semantic rules defined over some data set. Integrity constraints in relational databases are given as examples of such semantic rules. Like Dejaeger et al. (2010), Batini et al. (2009) also mentions two categories of integrity constraints which are intra-relation constraints and inter-relation constraints.

In the study of Dejaeger et al. (2010), *completeness* is referred to the extent of missing and duplicate values. Here, completeness implicitly inherits *uniqueness* dimension. Sometimes, those two dimensions are evaluated simultaneously in the literature. Batini et al. (2009) define completeness as the degree of inclusion of data describing real-world objects in a given data collection. Redman (1996) similarly defines it as the degree of inclusion of values in the data collection. Definition of completeness in Wand and Wang (1996) somewhat differ as they define it in terms of information systems. They refer it as the ability of information systems to represent every meaningful state of real systems. Definition of Wang and Strong (1996) is based on tasks concerned in terms of sufficiency in breadth, depth and scope. Jarke et al. (1995) define completeness according to data warehouse requirements as the rate of real information captured in data warehouse. Bovee et al. (2001) are interested in completeness of entity data as such information for entity description should include all necessary aspects of the entity. Liu and Chi (2002) refer completeness to all values supposed to be collected as per “collection theory”. Naumann (2002) has completeness definition similar to that is referred in Dejaeger et al. (2010) as the ratio of number of non-null values in data source to the size of universal relation. Completeness is usually related to not having null or missing values in relational databases. However, missing data can be attributed to different reasons. Existence or missing of data could be either certain or ambiguous.

Time-related dimensions are considered differently in the literature. Time-related aspects of data quality outspoken in the literature are *currency*, *volatility* and *timeliness*. Dejaeger et al. (2010) refer to currency as immediate update of data, volatility as frequency of updates of date and timeliness as retrieval of recent data upon specific request. Wand and Wang (1996) refer to timeliness aspect to delay between change in real world state and corresponding modification in information system state. Redman (1996) focuses on the currency aspect and defines it as the degree of being update of data considering the fact that it takes some time to retrieve the correct and updated value. Redman’s definition of currency resembles to Wand and Wang’s definition of timeliness in terms of attribution to delay in update in contrast to Dejaeger et al. who consider two terms as different concepts. Wang and Strong (1996) maintain the focus on task in defining time-related dimensions. They define timeliness as the extent of appropriateness of data age for a given task. That definition is consistent to that referred in Dejaeger et al. Liu and Chi (2002) also define timeliness aspect in accordance with Wang and Strong and Dejaeger et al. as the extent of sufficiency of data in being up-to-date for a specific task. Bovee et al. (2001) suggest timeliness has two components that are currency and volatility. Currency is considered measure of information age which corresponds to timeliness definition of Wang and Strong, Liu and Chi and Dejaeger while volatility is considered measure of information instability, that is, the frequency of the change of a value. Jarke et al. (2005) suggest two time-related dimensions which are currency referring to entrance date of information to data warehouse and volatility referring to time period for validity of data in real world. Volatility definition of Jarke et al. implies frequency mentioned in Bovee et al. and Dejaeger et al. Nauman’s (2002) definition of timelines which is the average age of data in a source resembles to that of Jarke et al. except for average calculation involvement.

DQ dimensions are not limited to accuracy, consistency, completeness and time-related dimensions. Dejaeger et al. (2010) count comprehensibility and security as other frequently mentioned dimensions in addition to those dimensions. Wang and Strong (1996) group fifteen DQ dimensions under four DQ categories as important data quality dimensions as a result of statistical analysis of interviews. These DQ categories are intrinsic DQ, accessibility DQ, contextual DQ and representational DQ. Intrinsic DQ refers to the extent to which data values are in conformance with the actual values. Contextual DQ refers to the extent to which data are applicable to the task of the data user. Representational DQ refers to the extent to which data are presented in clear manner. Accessibility DQ refers to the extent to which data are available. Moges et al. (2011) added three more dimensions (alignment, actionability and traceability) to those selected by Wang and Strong while exploring DQ dimensions relevant to credit risk assessment. Batini et al. (2009) gathered and grouped DQ dimensions used by various methodologies while comparing these methodologies. DQ dimensions that are mostly cited in the literature are compiled and presented in APPENDIX A.

## 2.2 Data Quality Assessment

The significance of DQ varies among different organizations based on the role and the significance of IS within their organizations. Gozman and Currie (2015) identify data aggregation and management as one of the IS capabilities that an organization should achieve. Maturity level of the organization in that IS capability also reflects the attitude of the organization towards DQA. As the maturity level of the organization in the IS capability of data aggregation and management increases, advanced controls over the quality of data mount up. The significance of DQA grows as organizations put more emphasis on the achievement of IS capabilities.

Data quality dimensions are identified and defined keeping in mind the goal of the task or context in an organization. Yin et al. (2014) remark that the selection of various DQ dimensions plays substantial role in the process of DQA, and emphasize on establishing multi-dimensional DQA system avoiding focusing on an individual dimension. Woodall and Parlikad (2010) define DQA as the process of "obtaining measurements of DQ and using these measurements to determine the level of DQ improvement required". Thus, identifying data quality metrics is crucial in the assessment of data quality and taking necessary actions for improvement of data quality. Besides DQ metrics, questionnaires can also be used for DQA. Lee et al. (2002) developed a methodology for information quality management to assess quality of data using questionnaires. The study is focused on assessing information quality independent from the domain via subsequent questionnaires in order to identify relevant quality dimensions for benchmarking and to obtain information quality measures which are to be compared to benchmarks. Use of either DQ metrics or questionnaires implies that DQA can be based on objective measurement or subjective judgment. Pipino et al. (2002) described objective and subjective assessment of data quality and presented how to combine them. They proposed three prevalent functional forms for objective assessment of DQ which can be used to develop DQ metrics to be used in practice. The functional forms addressed in the study are *simple ratio*, *min or max operation*, and *weighted average*. These functional forms are stated to be crucial in developing metrics for DQA in the study. Simple ratio is used to measure the ratio of desired outcomes to total outcomes. Accuracy, consistency and completeness dimensions take this form according to the study. We also use the simple ratio form in the measurement phase of the present study while developing DQ metrics for credit risk data but we measure "undesired outcomes rather than desired outcomes.

Increasing diversity and complexity in these techniques due to evolving nature of information system lead to development of different assessment methods in order to systematically perform data quality assessment. Batini et al. (2009) attribute such differentiation and specialization in DQA methods and techniques to the evolution of information and communication technologies from monolithic structure to network-based structure which leads to growth in complexity of DQ. Therefore, studies on DQA focus on subset of DQ issues rather than all DQ issues.

Besides DQA methods specialized according to various subjects, hybrid approaches are also studied in order to span more than one field in DQA. Woodall and Parlikad (2010), and Woodall et al. (2013) proposed such a hybrid approach in order to assess and improve data quality of not only in a specific context but within various contexts. Since some of the existing assessment techniques cover only some specific area and some of them are more general to address specific requirements, the hybrid approach is presented to generate usable assessment techniques for specific requirements using the activities of assessment techniques. These activities are identified via DQA techniques existing in the literature.

Borek et al. (2011) present classification of data quality assessment methods and map them according to taxonomy of DQ problems which are gathered from previous studies in terms of context dependence and data and user perspectives. Their study focuses on the existing methods such as data profiling, schema matching, lexical analysis and semantic profiling. These methods are mapped to the most common DQ problems. Mapping tables are constructed separately for context dependent and context independent problems.

Implementation of DQA approaches is spread over different areas. Wang (1998) proposed a DQA approach named "Total Data Quality Management" treating information flowing through a certain organization as an information product as inspired from manufacturing process (See Section 2.3). The approach is not specific to any context although there are many references to TDQM by studies from various fields from health to finance (Moges et al. (2013) and Kerr (2006)). Jeusfeld et al. (1998) present an approach that studies design and analysis of quality information for data warehouses by building a quality metadata model for warehouses that can be used for design of quality and analysis of quality measurements. English (1999) also proposes an approach called "Total Information Quality Management" to assess information quality of data warehouses taking economic feasibility into account in consolidating data sources. Loshin (2004) also considers economic feasibility aspects in evaluating the cost-effect of poor quality data based on data quality scorecards. Long and Seko (2005) propose a cyclic-hierarchical approach for assessment of the quality of health data with a data quality framework and analysis of frequency of data access. Falorsi et al. (2003) developed an approach to be used in databases of local public administrations in order to collect high quality statistical data on citizens by providing quality of data integrated from different local databases. Su and Jin (2004) proposed a method to assess product information quality based on activities in manufacturing companies. The assessment and improvement of product information quality are performed in accordance with the organizational goals of the company. Scannapieco et al. (2004) studied DQA in cooperative information systems and DQ challenges faced in such systems. Batini and Scannapieco (2006) proposed a complete data quality methodology that helps to select optimal data quality improvement process with maximum benefits within the given budget limits. Eppler and Münzenmaier (2002) provided a framework for the assessment of web data. De Amicis and Batini (2004) studied the assessment of data quality in finance field and define quality metrics specifically for financial data using both quantitative objective and qualitative subjective assessments to identify quality issues and select suitable activities for data quality improvement. Bai et al. (2012) present an approach involving Markov decision process in order to manage the risks related to the quality of data in accounting management systems.

## 2.3 Total Data Quality Management (TDQM) Program

Total Data Quality Management (TDQM) can be regarded as the first well-founded approach related to data quality assessment proposed by Wang (1998). Wang derived TDQM from Total Quality Management (TQM) which is used for product quality. This approach consists of four phases which are definition, measurement, analysis and improvement. Implementation of the TDQM cycle aims to improve quality of information product (IP) continuously. Definition phase involves identifying information quality (IQ) dimensions and IQ requirements. Measurement phase is related to production of IQ metrics. Analysis phase is concerned with identifying fundamental causes of IQ problems and measuring the impact of poor quality of information. The last phase of the cycle, improvement phase, is devoted to develop techniques for IQ improvement. Wang inspired by the terminology of TQM, defines IP as the output produced by information manufacturing system (IMS). Such description leads Wang to identify four roles relevant to IP and IMS. These roles are *information suppliers* who create or collect data for the IP, *information manufacturers* who design, develop or maintain the data and system infrastructure for the IP, *information consumers* who use the information for their business and *IP managers* who are responsible for managing whole information production process throughout the information life cycle. TDQM is performed iteratively through the cycle implying that fitness of data for the use of IP customers should be checked at each definition phase according to changing requirements.

Use of TDQM is adopted in different fields due to its adaptability to the requirements of those fields. Finance or banking is one of those fields. More specifically, TDQM can be used in credit risk management. Studies of Moges et al. (2011) and (2013), and Moges (2014) can be given as the examples of such use.

Thus, in order to specify data quality requirements, outline of the credit risk context should be pictured. Determination of boundaries for credit risk will contribute to identify data taxonomies and DQ dimensions relevant to such taxonomy.

## 2.4 Overview of Banking Risks and Credit Risk Management

Identification and classification of risks under capital requirement phenomenon is based on Basel Accords. Viable framework for quantitative aspects of capital standards is Basel II (BCBS, 2006). The framework presents standardized terminology and taxonomy for calculation of risk exposure to determine capital holding level for banks. This standard for identification and classification of risk allows banks, the most important component of the financial sector, to design their IT infrastructure in accordance with international standards for risk management system. Although the core function of banks is not risk management but rather allocation of credits and financial transaction in various financial markets, it is hard to survive in the system and maintain their functions in a sustainable manner without involvement of a sound risk management system. Therefore, they have to incorporate risk management system into their information system and provide reconciliation of risks with accounting information. This reconciliation contributes to achievement of building risk management system with controllable and measurable size within the standards predefined by the framework.

The Basel framework is a widely accepted international standard; therefore, stands at the backbone of risk management activities and IT requirements relevant to such activities. The framework consists of three pillars as shown in Figure 1. The very first pillar handles quantitative aspects of risk management, namely minimum capital requirements. The second pillar is regarding key principles of supervisory review, risk management guidance and supervisory transparency and accountability produced by the Basel Committee with respect to banking risks. The third pillar is related to market discipline which involves guidance of public disclosure requirements for banks in order to provide transparency of bank information to market participants.

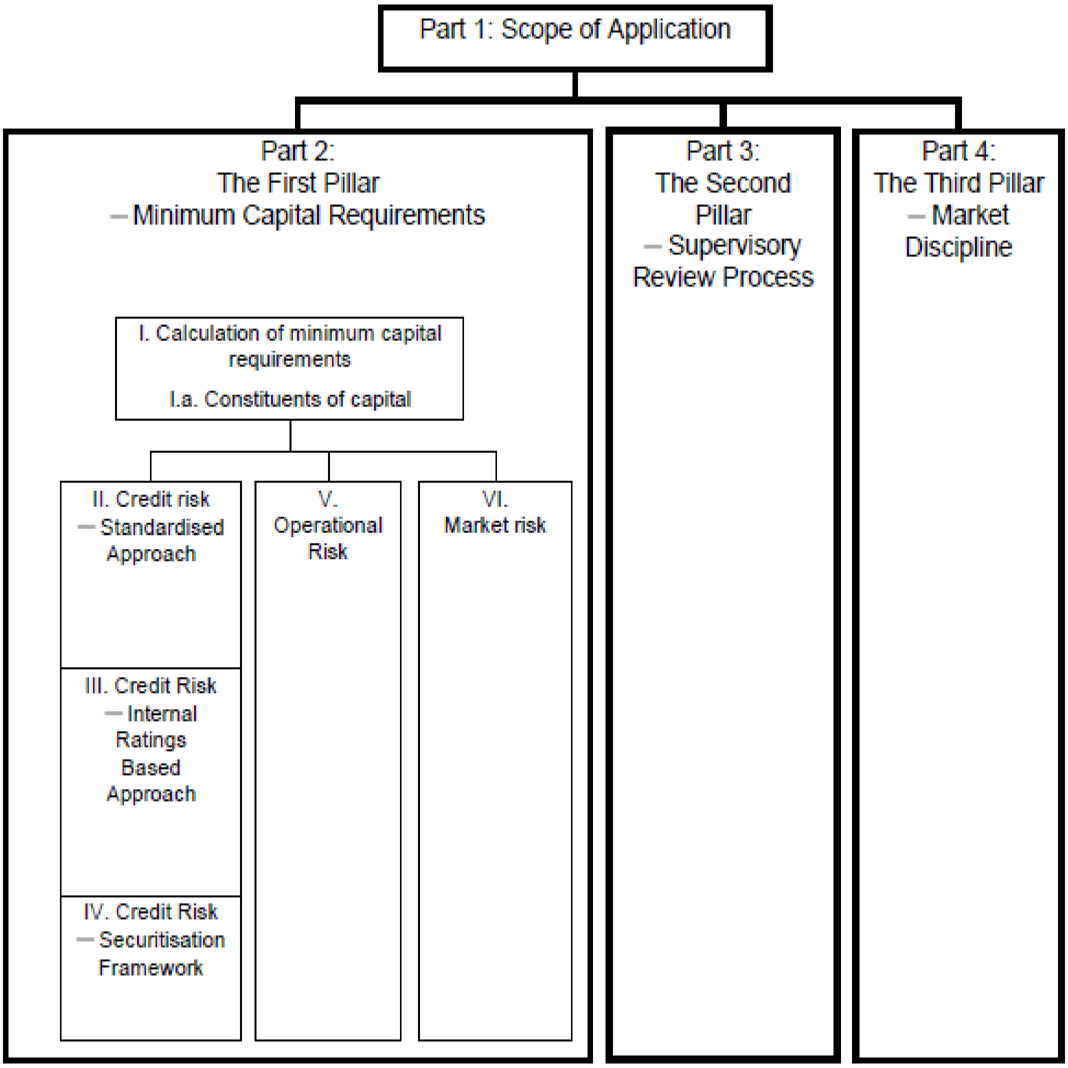

Part 1: Scope of Application
Part 2: The First Pillar – Minimum Capital Requirements
Part 3: The Second Pillar – Supervisory Review Process
Part 4: The Third Pillar – Market Discipline
I. Calculation of minimum capital requirements
I.a. Constituents of capital
II. Credit risk – Standardised Approach
III. Credit Risk – Internal Ratings Based Approach
IV. Credit Risk – Securitisation Framework
V. Operational Risk
VI. Market risk

**Figure 1** The structure of Basel II framework (BCBS, 2006)

Quantification and calculation of the risks are ultimately aggregated and represented as capital adequacy ratio (CAR). CAR is defined as the regulatory equity divided by overall sum of credit risk exposure amount, market risk exposure amount and operational risk exposure amount (BRSA, 2014). CAR is the most important overall quantitative indication of how much capital is hold against the calculated risks of the bank. CAR must be above specific threshold, i.e. minimum regulatory ratio, which is imposed by the supervisory authority over the banks in accordance with the Basel Accords (the framework).

As the definition of Capital Adequacy Ratio implies there are three constituents of capital adequacy other than regulatory equity. These are credit risk, market risk and operational risk. Those risk types addressing exposures of banks are the subject of capital requirement calculation.

The Basel framework refers to credit risk as the risk of loss on an obligation due to default of the obligor and thus failing to make payments of that obligation. In calculation of credit risk exposure amount; credit type, risk weight associated with that credit type or the credibility of the obligor, collateral types if exist are important parameters. The framework refers to market risk as the risk of loss of positions in banks' assets due to fluctuations in market prices. Equity risk, commodity risk, interest rate risk and currency risk are under this category. It refers to operational risk as the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events (BCBS, 2006). Credit risk is the biggest constituent of overall risk-weighted exposure amount (about %90) compared to market risk and operational risk in terms of their amount (see Figure 2). Each risk type requires the creation or collection of its own data set based on data entities identified under the risk type. This study will focus on data sets created or collected for measurement of credit risk.

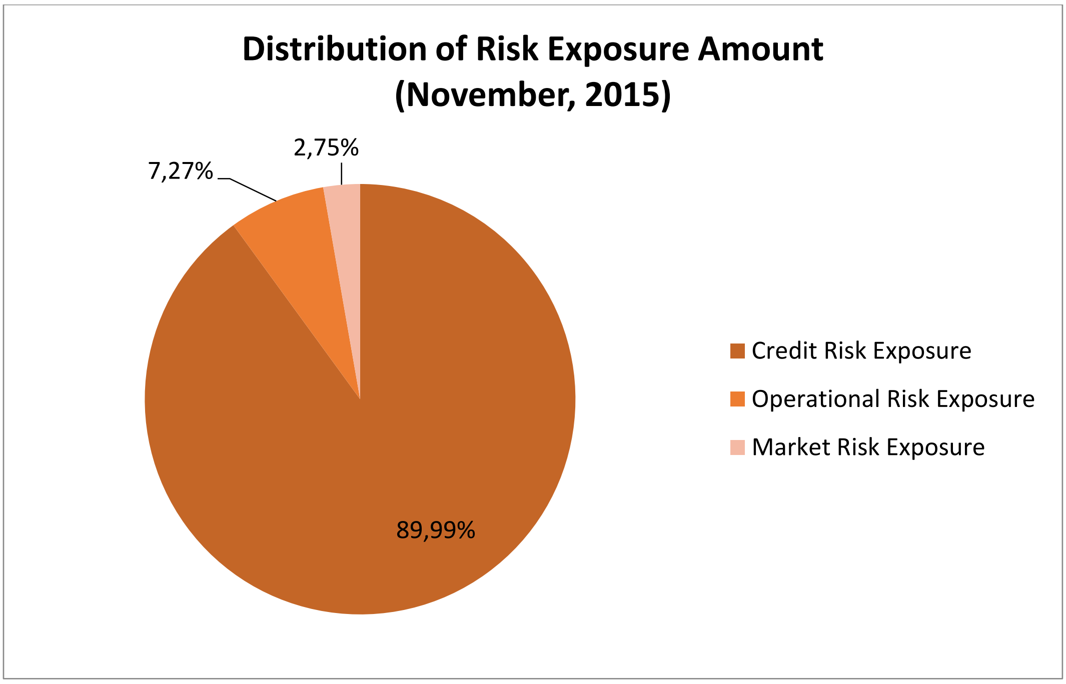


**Figure 2** Aggregate share of risk types in terms of their amount in the Turkish banking sector (November, 2015)[2]

Thus, CAR has four components: regulatory equity in the numerator and sum of risk-weighted amounts of credit risk, market risk and operational risk in the denominator.

[2] BRSA, Interactive monthly bulletin for Turkish Banking Sector, http://ebulten.bddk.org.tr/ABMVC/tr/Gosterim/Gelismis

Regulatory equity is obtained by adding/subtracting specific accounting items to/from accounting equity (BRSA, 2014). On the other hand, risk-weighted amounts related to credit risk, market risk and operational risk are calculated via different approaches and methods according to risk type and calculation complexity in Basel II (See Table 1).

Calculation approaches for each risk type shown in Table 1 demonstrate an evolution from the basic approach to the advanced approach for each risk type. Basic and standard approaches are deterministic implying that parameter values are predefined based on risk nature and mandated by regulations. That is, standard risk weights which are derived from the external ratings given by credit rating agencies (CRAs) are employed. Advanced approach is usually driven by statistical models. It has a stochastic nature implying that it requires data gathering and statistical estimation methods applied on that data set. Ratings are generated internally by this stochastic approach. This approach sometimes involves overrides, i.e. expert judgment that can manipulate results generated statistically. Each approach requires different data taxonomies and requirements. In terms of data quality assessment, criticality of data quality and type of DQ dimensions may change due to changing complexity of data requirement while certain quality requirements still remain effective.

**Table 1** Risk calculation approaches according to Basel II (BCBS, 2006)

| Complexity Level | Credit Risk | Market Risk | Operational Risk |
|---|---|---|---|
| Simple | Simplified Standard Approach | N/A | Basic Indicator Approach |
| Medium | Standard Approach | Standard Method | Standardized Approach |
| | | | Alternative Standardized Approach |
| Advanced | Foundation Internal Rating Based Approach | Value at Risk Models | Advanced Measurement Approaches |
| | Advanced Internal Rating Based Approach | | |

## Risk Function

Capital requirement of a bank for credit risk exposures can be calculated via two basic approaches according to the Basel framework. These are standard approach (SA) and internal rating based (IRB) approach. The basic difference between them is the determination of risk weights of an exposure. While only external ratings given by CRAs are used in the risk function under SA, internal ratings are used in the risk function under IRB approach. IRB approach has specific risk functions including statistical parameters and correlation terms. Comparison of SA and IRB approach in terms of their approach to risk quantification is given in Table 2. Fundamental factors that somewhat affect the credit risk function are worked out and compiled from the rules enforced in the Basel framework, and outlined in Figure 3.

Figure 3 reveals that there are three main components characteristics of which constitute the drivers of credit risk function. These components can be candidates for root data tables which support credit risk management practices. Those candidates should be taken into consideration in design and development of data architecture and IT infrastructure of banks for data governance, data quality management and credit risk management purposes. The present study will consider those candidates in identification of data taxonomy for credit risk data in the definition phase of the approach proposed below in Section 3.2.1.1.

**Table 2** Comparison of SA and IRB approach

| **Comparison item** | **Standard Approach** | **IRB Approach** |
|---|---|---|
| Regulatory capital requirement for credit risk | 8% × ∑ Risk-weighted assets (RWA) | 8% × ∑ Risk-weighted assets (RWA) |
| Risk weights based on | External ratings | Internal ratings (function of PD* and LGD**) |
| Risk function | Deterministic | Stochastic |
| *PD: Probability of Default (statistically obtained from dataset)<br>**LGD: Loss Given Default (statistically obtained from dataset or provided by the regulation) | | |

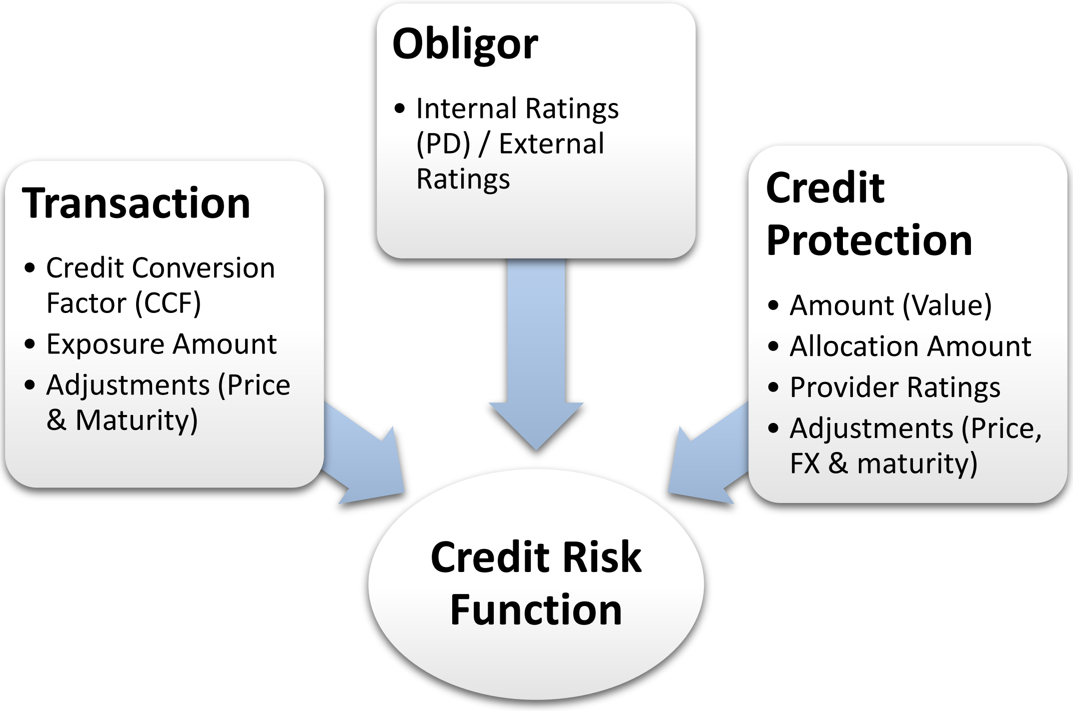

Obligor
• Internal Ratings (PD) / External Ratings
Transaction
• Credit Conversion Factor (CCF)
• Exposure Amount
• Adjustments (Price & Maturity)
Credit Protection
• Amount (Value)
• Allocation Amount
• Provider Ratings
• Adjustments (Price, FX & maturity)
Credit Risk Function

**Figure 3** Risk components appearing in risk function

## 2.5 DQA in Credit Risk Management

One of the business sectors most closely involved with DQA is the financial sector due to strong dependence of banking business to processing of huge chunks of data belonging to investors and customers. Yin et al. (2014) assert that DQA has become an indispensable part of data quality management in the banking sector.

Basel II and Basel III frameworks also address importance of data quality management and data governance under appropriate and well-established MIS as they become crucial aspects of risk management practices due to requirement for producing and dealing with huge amount of data related to banks' risk exposures (BCBS, 2006). For sound risk management, banks should ensure the quality of those data and manage the bulk of the data properly.

Data quality management and assessment play an important role for sound and safe financial system in which financial risks are controlled and mitigated. Gozman and Currie (2015) count data aggregation and management as one of the IS capabilities that a financial organization should achieve in order to manage and support governance, risk and compliance. Capability of data aggregation and management is the key for ensuring DQ of a financial organization.

According to the BCBS, a sound risk management system should have appropriate MIS at the banking sector and bank-wide level.

Financial institutions, particularly banks, have to identify and control risks to which they are exposed due to their operations in order to maintain their functions in a safe and sound manner. Therefore, they need to identify and quantify these risks clearly. Risk types relevant to the financial sector are identified in the Basel II framework issued by the Basel Committee (BCBS, 2006). The framework consists of three pillars which are minimum capital requirements (Pillar 1), supervisory review process (Pillar 2) and market discipline (Pillar 3). Quantifiable risks that affect calculation of regulatory capital requirement lie under Pillar 1. These risks are credit risk, market risk and operational risk. These risks have been defined above in Section 2.4. Banks hold capital in order to manage these risks. There are also other risk types referred in Pillar 2 such as systemic risk, concentration risk, liquidity risk, reputational risk, strategic risk, legal risk and residual risk; however, these risks are not considered in calculation of the capital requirement since they are hard to quantify.

There are a handful of studies focusing on DQA in credit risk management in the literature. Studies performed by Moges et al. (2011) and (2013), Moges (2014), Bonollo and Neri (2011), Dejaeger et al. (2010), and Yin et al. (2014) emerge as the prevailing ones in this subject.

Moges et al. (2011) identified important data quality dimensions for credit risk assessment using surveys conducted with credit risk managers of 150 financial institutions sampled out from 500 financial institutions across the world. Findings and statistical analysis of the survey revealed most important DQ dimensions from the perspective of credit managers. The study also identified major DQ challenges and their causes in financial institutions. Multiplicity of data sources and inconsistencies in data value and format are found to be the most repeated problems within those institutions. In addition, manual data entry operations emerged as the major cause of those problems. Although the study suggests the implementation of TDQM methodology proposed by Wang (1998) and consisting of the DQ definition, measurement, analysis and improvement phases, it only focuses on DQ definition phase in which DQ dimensions are determined via statistical analysis of the results of interviews. It does not go beyond exploring DQ dimensions important for credit risk assessment and identifying DQ challenges and their causes. Moges et al. (2013) and Moges (2014) took the study forward by further exploring subsequent phases of TDQM. They identified the most important DQ dimensions by conducting questionnaires to the financial institutions, and then they assessed DQ level of credit risk databases using these dimensions. After assessment of DQ of credit risk data, DQ challenges revealed by the DQA are analyzed and possible improvement actions are suggested. DQA of credit risk context is performed by a scorecard index developed. Definition, measurement and analysis phases of TDQM are performed using questionnaires rather than development of metrics. Statistical tests are used to identify the most important DQ dimensions. DQ levels of credit risk databases are evaluated by a weighted average model in which the distributions of the weighted averages of DQ categories are compared to each other based on a scale ranging from very good to worst. The scorecard index is used to assess DQ level and to identify problematic areas. In our study, we used DQ metrics identified by analyzing data taxonomy of credit risk data in accordance with Basel rather than questionnaires which constitutes the backbone of the studies of Moges et al. (2013) and Moges (2014).

Dejaeger et al. (2010) select the mostly explored six DQ dimensions in the literature instead of statistical analysis for the selection of DQ dimensions in order to analyze data quality of credit rating process in financial sector. Their study focuses on business processes in order to detect the critical errors likely to occur in these processes. The methodology of the study involves designing and using a questionnaire based on ETL (Extract Transfer Load) approach in which data creation, extraction, load and manipulation are performed in different processes through the data source and the destination database. The questionnaire consists of several questions that address various parts of ETL approach. Those parts are collection, analysis and warehousing aspects. Collection aspect involves comprehensibility dimension which deals with to what extent data format of source data is standardized, and consistency dimension deals with standardization of inconsistent data. Analysis aspect is related to data analysis and data transformation, and it involves comprehensibility and time dimensions. Warehousing aspect is related to conveying data transformed and analyzed to the following phases of the process. This aspect involves inconsistency and comprehensibility dimensions. Business Process Modelling Notation (BPMN) in combination with the questionnaire is used to visualize the process of credit rating in order to identify flow of data through the process. The DQ dimensions defined in the definition phase of our study analogous to those selected in the study of Dejaeger et al. (2010).

There are also approaches to DQA which combine both qualitative and quantitative aspects. Yin et al. (2014) present an approach based on analytic hierarchy process for the assessment of quality of banking data. The study proposes an evaluation index system in which weights of the coefficients of the indexes are determined by the method based on analytic hierarchy process. The indexes are used to evaluate the quality of banking data.

Bonollo and Neri (2011) examined issues related to data quality in banking based on regulatory requirements of the Basel framework and proposed best practice analysis to tackle these issues. The study proposes four-step analysis consisting of examination of silo organization of risk data, review of existing data quality regulations in the financial sector, best practice proposal regarding a centralized approach to risk data and the centralized data approach combined with a sensitivity technique for effective data quality strategies and indicators. The best practices for the governance of data quality proposed by the study focuses on two main approaches which are a centralized approach to data quality and the integration between risk and finance. The study also distinctively makes a proposal that can improve data quality metrics. The proposal involves definition of a data quality assessment process based on DQ dimensions in four macro steps. These steps are outlined as follows:

1. Definition of variables
2. Definition of DQ dimensions for each variable
3. Assignment of weights to data performing poor quality on certain dimension
4. Development of key quality indicators which can be derived from weighted averages of the results of quality examinations

One of the significant contributions of the study to the measurement of data quality is proposing key quality indicators which are generated from a bottom-up process. The aim is to perform data quality controls starting from bottom level and attain high level key quality indicators which should be weighted or rescaled with respect to their criticality in risk measurement. The present study also elaborates on that notion while developing quality performance indicators in Chapter 3.

## 2.6 Basel Document Related to Data Quality of Risk Data

As the 2007-2008 global financial crisis revealed the inadequacy of IS of financial institutions in managing their financial risks, the need for new regulatory obligations has emerged. Basel Committee on Banking Supervision (BCBS) which is responsible for preparation of international capital standards, i.e. the Basel framework, has been forced to revise the framework following the detrimental effects of the crisis. Supplementary rules to the framework have also highlighted the need for sound MIS of banks. Furthermore, the Committee has published a document titled “Principles for effective risk data aggregation and risk reporting” (2013). The paper suggests fourteen principles eleven of which are regarding banks and the rest are regarding supervision authority to strengthen risk data aggregation capabilities of banks and their risk reporting practices. The principles are accumulated in four sections. The framework of these principles and their aspects are given in Table 3.

.

**Table 3** Principles for risk data aggregation and risk reporting stated by BCBS (2013).

| Section | Principle No | Principle Aspect |
|---|---|---|
| *Overarching governance and infrastructure* | P1 | Governance |
| | P2 | Data architecture and IT infrastructure |
| *Risk data aggregation capabilities* | P3 | Accuracy and Integrity |
| | P4 | Completeness |
| | P5 | Timeliness |
| | P6 | Adaptability |
| *Risk reporting practices* | P7 | Accuracy |
| | P8 | Comprehensiveness |
| | P9 | Clarity |
| | P10 | Frequency |
| | P11 | Distribution |
| *Supervisory review, tools and cooperation* | P12 | Review |
| | P13 | Remedial action and supervisory measures |
| | P14 | Home/host cooperation |

The principles are specifically designed for risk data aggregation purposes and risk reporting practices. Although principles are addressed under four separate sections, they are strongly interlinked; i.e. improvement in a section will greatly and positively affect the others. Strong risk data aggregation capabilities lead to production of high quality of risk management reports. Governance and infrastructure encompass these functions and operations implying that strength and development at governance and infrastructure will significantly contribute to enhancement in the risk aggregation and risk reporting capabilities.

Principle dimensions under risk data aggregation capabilities and risk reporting practices categories strongly align with DQ dimensions explored in DQ assessment methods. Accuracy and integrity of risk data can be provided by automation of aggregation of such data which will minimize risk of making errors during aggregation. Completeness of risk data requires proper aggregation of risk data obtained from all units or groups of the bank. Timeliness of risk data requires risk data being up-to-date which can be significant for some risk data. Comprehensiveness related to coverage of all material risk data.

Governance requires definition of the hierarchy of roles within the bank. Data architecture and IT infrastructure require modeling of risk management system regarding the roles and responsibilities of the stakeholders of the system. Thus, the first two principles require detailed requirement analysis which is outside the scope of the present study. Our focus will be on the fulfillment of the principles belonging to risk data aggregation capabilities and risk reporting practices. Supervision aspect is related to monitoring other principles. Therefore, our approach will encompass the principles which can directly be monitored using quantitative data and techniques related to banking risks. Appropriate data quality dimensions which will be selected in the definition phase of our approach will be aligned with the principles regarding risk data aggregation and risk reporting.

Implementation of those principles requires certain maturity level in IS capabilities of banks. Gozman and Currie (2015) have identified nine IS capabilities underpinning activities for managing governance, risk and compliance in accordance with regulatory obligations. The IS capabilities derived from the studies conducted on several financial organizations and IS vendors involve administering automated controls, underpinning ethical practice, monitoring and reporting governance, risk and compliance outcomes, data aggregation and management, sourcing governance, risk and compliance functionality, managing service providers, determining best practices, IS leadership, and prioritization of activities for achieving higher maturity levels and transitioning abilities of organizations to higher maturity levels.

# CHAPTER 3

# METHODOLOGY

This chapter is devoted to study of how to adapt and apply TDQM approach to credit risk management context from IS viewpoint and to build content of phase of the approach. Each phase of TDQM is specialized and enriched for the purposes of DQA of credit risk data. Reasoning, objectives, assumptions and requirements for application of TDQM are also discussed in this chapter.

## 3.1 Reasoning, Objectives and Requirements of the Proposed Approach

### 3.1.1 Reasoning

Data quality of banking risks must be ensured in order to accurately quantify and measure the risks for which banks require to hold capital, and to calculate regulatory capital requirement as a result of those risks. The largest portion of exposures of banks belongs to credit risk. Due to those reasons, there is a need for a special and comprehensive DQA method that can be used to assess quality of credit risk data. Although there are efforts focusing on DQA of credit risk data in the literature as outlined in 2.5, there is still need for an alternative approach in order to thoroughly assess data quality of the credit risk data. There are various approaches proposed to assess DQ of different contexts which are explored in 2.2. TDQM is independent from the context, i.e. they can be adjusted for different contexts in order to assess DQ of this context (Woodall & Parlikad, 2010). There are also various approaches specifically designed for certain fields such as data regarding health sector, demography or web services. There are also valuable studies attempting to assess DQ of credit risk context. These studies have been outlined above in Section 2.5. Some of these studies (Moges et al., 2011 & 2013, and Moges, 2014) adopt TDQM in assessment of DQ of financial risk data, specifically credit risk. These studies involve empirical studies using questionnaires rather than developing objective DQ metrics. One study addresses the use of key quality indicators based on data quality measurements. However, there is no detailed procedure for how to obtain such indicators. This reveals a clear need for a thorough assessment of data quality of credit risk data via data quality metrics. The structure of TDQM allows development of such DQ metrics. Another reason for adoption of TDQM is that it is a context-independent approach which provides flexibility for adaptation of credit risk context. Its phases are suitable for comprehension and analysis of data quality aspects. Definition phase of the approach is based on the DQ dimensions studied by Wang and Strong (1996) which identify the dimensions relevant to credit risk. Moreover, the continuous improvement cycle of TDQM enables alignment of the approach with the increasing sophistication of credit risk data.

### 3.1.2 Objectives

DQA to be applied aims to assess data quality of credit risk data by identifying risk data content and data taxonomy in terms of IT infrastructure first, then determining relevant DQ dimensions relevant to the risk data, building metrics for the dimensions identified so that underlying problems related to data quality be revealed and explored. Iterative analysis of data quality problems will contribute to enhance standardization of risk data structure, reduce inconsistencies stemming from discrepancies among multiple data sources used and provide accuracy of data. Proficiency of data processing tools for credit risk management will be evaluated from an IS perspective.

### 3.1.3 Assumptions and Requirements

It is crucial to trace the source of the risk data in order to control quality of it. Risk data is generated from different sources. For instance, information regarding exposure amount is obtained from the accounts retrieved from accounting sheets and other necessary information relevant to risk measurement such as ratings, client information (real person or an entity) of which signed documents or official papers are usually obtained by branches and other information obtained by various entities. Therefore, IT infrastructure of the bank organization is supposed to provide reliable access to necessary information. Moreover, Roles, responsibilities and authorizations within the bank organization should clearly be identified and assigned. These aspects are addressed in the BCBS document discussed in Section 2.5. The approach assumes that the IT infrastructure and the roles contributing the generation and retrieval of risk data are identified in accordance with the principles related to governance and infrastructure as elaborated in Section 2.5.

## 3.2 Phases

In this section, we build our DQA methods on the phases of TDQM in order to assess quality of credit risk data in terms of DQ dimensions to be specified. As cited in Section 2.3, TDQM consists of four phases: Definition, measurement, analysis and improvement. Definition phase of TDQM involves definition of DQ dimensions. Measurement phase is devoted to development of DQ metrics in order to assess DQ of based on the dimensions defined in Phase 1. Analysis phase involves analysis of DQA results and investigate underlying causes of poor DQ. Improvement phase contains suggestions for improvement of DQ of poor quality data based on the causes identified and analyzed (Wang, 1998).

Below, we are going to elaborate on the content of each phase according to credit risk context. The content of each phase is outlined in Table 4.

Brief explanation for each phase is provided below.

*Phase 1: Definition of data quality*

The first phase of the approach defines the scope of the approach, classifies the relevant credit risk data context based on the description of the context in Section 2.4 and then defines the relevant data quality dimensions. The data taxonomy is described in accordance with Basel Accords regarding credit risk outlined in Section 2.4. Alignment of the data taxonomy with IT requirements is also addressed in this phase. Moreover, viable data sources that feed data required for credit risk management are identified in this phase.

Once critical objects and attributes are determined, data quality dimensions relevant to these attributes of credit risk data should be determined. DQ dimensions explored in Section 2.1.2 and principle set of BCBS outlined in Section 2.5 will guide us to determine these DQ dimensions with focus to the findings of impact analysis.

*Phase 2: Measurement of data quality*

Using the DQ quality dimensions specified in the first phase, performance metrics are constructed in this phase. These metrics refer to the rates of violation of data quality requirements.

Since banking credit risk data consists of quantitative data and can be presented in referential database tables, data quality assessment methods used in databases can easily be implemented. Such methods can include column analysis, cross-domain analysis, data validation, domain analysis, lexical analysis, matching algorithms, primary key and foreign key analysis, schema matching, and semantic profiling (Borek et al., 2011). Implementation of such methods will be used to calculate performance metrics specified in this phase. DQA will be based on individual and composite quality performance indicators constructed by transforming metrics in this phase.

**Table 4** Outline of the customized TDQM approach for banking credit risk data

| ***Phase Name*** | ***Content*** |
|---|---|
| *Definition of DQ* | • Identification of data taxonomy and data sources for credit risk management<br>o Identification of entities and its attributes<br>o Identification of data sources of the attributes<br>• Definition of data quality dimensions for credit risk data context |
| *Measurement of DQ* | • Development of performance metrics for DQ dimensions<br>• Identification of measurement methods/techniques for performance metrics<br>• Development of KQPIs and CQPIs |
| *Analysis of DQ* | • Analysis of DQA results obtained from KQPIs and CQPIs<br>• Identification and analysis of DQ problems |
| *Improvement of DQ* | • Development of improvement techniques to propose solution for the problems |

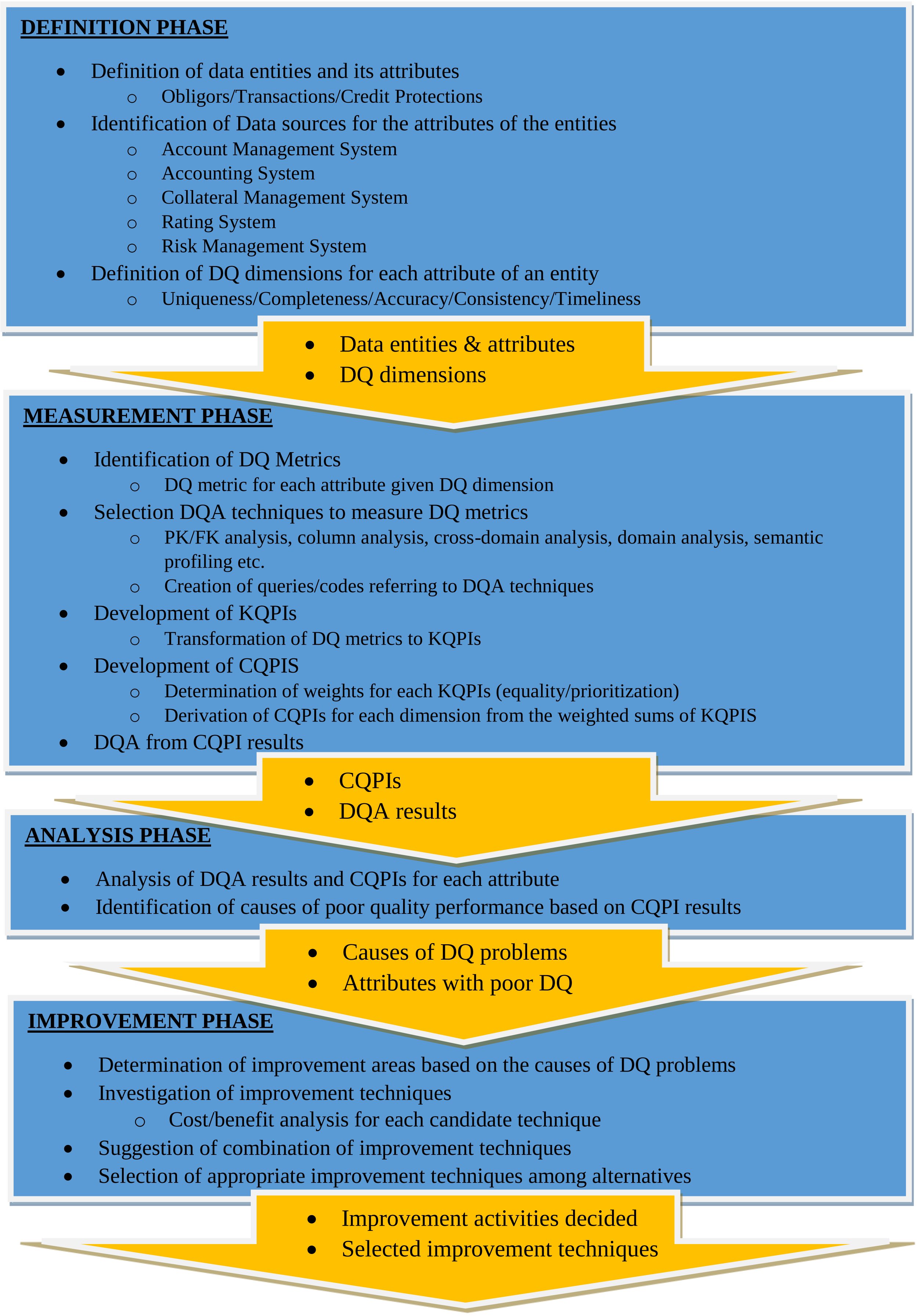
*Phase 3: Analysis of data quality*

According to the performance results of the DQ assessment obtained from quality performance metrics utilized in the second phase, DQ problems, if exist, and their underlying causes are identified and classified in order to develop strategies for improvement in such problematic areas.

*Phase 4: Improvement of data quality*

The last phase concentrates on proposals for solution strategies and techniques for the improvement areas decided. Performance metrics developed in the second phase are binding for selecting improvement techniques.

Relationship and flows among the phases constructed in the present study and proposed for DQA of credit risk management context are outlined in Figure 4.



**DEFINITION PHASE**

- Definition of data entities and its attributes
  - Obligors/Transactions/Credit Protections
- Identification of Data sources for the attributes of the entities
  - Account Management System
  - Accounting System
  - Collateral Management System
  - Rating System
  - Risk Management System
- Definition of DQ dimensions for each attribute of an entity
  - Uniqueness/Completeness/Accuracy/Consistency/Timeliness

- Data entities & attributes
- DQ dimensions

**MEASUREMENT PHASE**

- Identification of DQ Metrics
  - DQ metric for each attribute given DQ dimension
- Selection DQA techniques to measure DQ metrics
  - PK/FK analysis, column analysis, cross-domain analysis, domain analysis, semantic profiling etc.
  - Creation of queries/codes referring to DQA techniques
- Development of KQPIs
  - Transformation of DQ metrics to KQPIs
- Development of CQPIS
  - Determination of weights for each KQPIs (equality/prioritization)
  - Derivation of CQPIs for each dimension from the weighted sums of KQPIS
- DQA from CQPI results

- CQPIs
- DQA results

**ANALYSIS PHASE**

- Analysis of DQA results and CQPIs for each attribute
- Identification of causes of poor quality performance based on CQPI results

- Causes of DQ problems
- Attributes with poor DQ

**IMPROVEMENT PHASE**

- Determination of improvement areas based on the causes of DQ problems
- Investigation of improvement techniques
  - Cost/benefit analysis for each candidate technique
- Suggestion of combination of improvement techniques
- Selection of appropriate improvement techniques among alternatives

- Improvement activities decided
- Selected improvement techniques

**Figure 4** Outline of the phases of TDQM adapted for credit risk context

### 3.2.1 Phase 1: Definition of data quality

#### 3.2.1.1 Identification of Data Taxonomy for Credit Risk Data

Data taxonomy of credit risk can be designated based on the outline of the information regarding credit risk context derived from the Basel framework in Section 2.4. Three fundamental entities emerge as the drivers of credit risk function are analyzed. These are the obligor, the transaction and the credit protection. Obligors are the clients of the bank who make transaction with the bank. The transaction itself is the very basic element of the exposure. Credit protection is used to reduce exposure amount. It can be either funded or unfunded. Funded credit protection is usually provided via several assets which can be turned into cash in case of default of the obligor. Unfunded protection is, on the other hand, guarantee provided by third parties. Therefore, exposure amount of a transaction can be determined by three entities. To quantify an exposure, the bank has to accumulate relevant information specific to the obligor, the transaction and credit protection if exists. Banks must conveniently access this kind of information in order to quantify and calculate their exposures in robust manner. Each entity has its own effect on overall risk-weighted exposure amount depending on its characteristics. Basic characteristics of these entities are outlined in Figure 5. Well-establishment of the content of these entities contributes to create beneficial relationship tables which can effectively be used in credit risk management. Such a relationship requirement is implied in Figure 3 as the risk function is composed of components provided by information regarding obligors, transactions and credit protections.

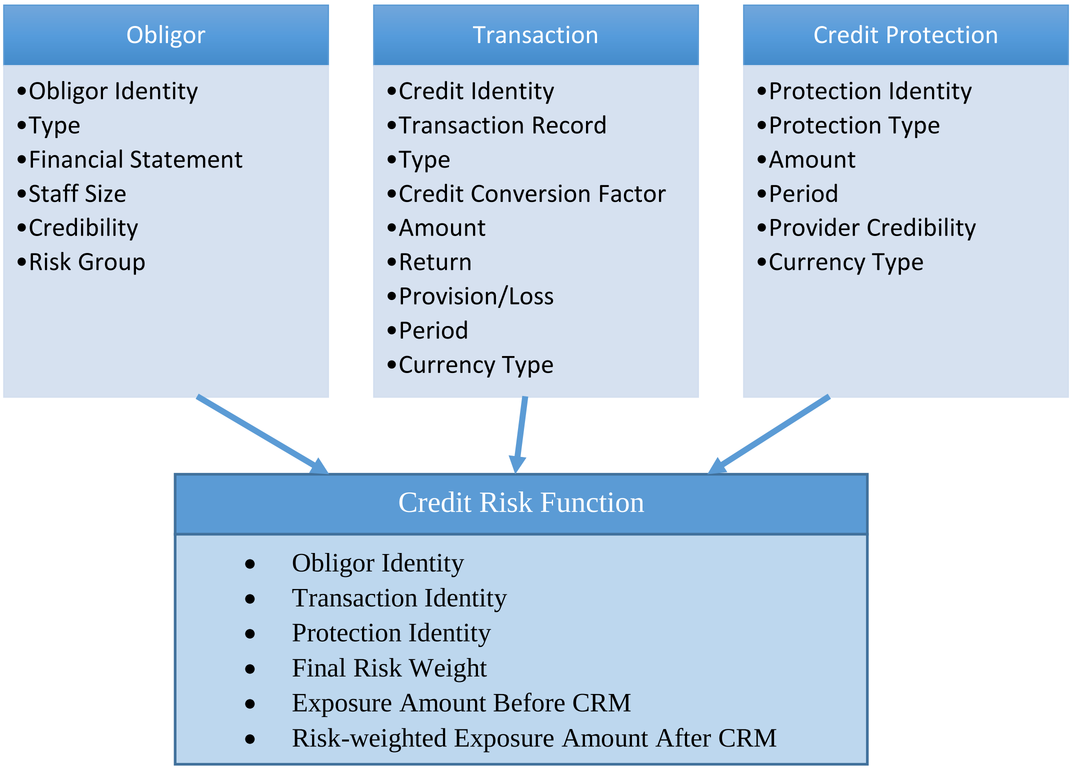


**Figure 5** Basic characteristics of an obligor, transaction, credit protection and credit risk function

*Obligor characteristics*

Characteristics of an obligor are identity, type, financial statement and credibility. Identity of an obligor can be determined by its account number, tax ID and country. Type of the obligor specifies the legal nature of the obligor. The type can be a central bank, a central government, a regional government, a public entity, a bank, a corporate, a SME or an individual real person at all. Financial statement of the obligor specifies its revenue or asset size. Staff size attribute is only applicable to non-real persons. Credibility of the obligor can be determined via internal and/or external ratings. Credibility can be expressed as risk weight of the obligor in data tables. If SA is used, determination of risk weights from the external ratings and regulations is straightforward. However; if IRB approach is used, determination of risk weights is a bit tricky. PD and LGD parameters should be used in the risk function. Risk group of the obligor is required to specify the parent or subsidiary entities of the obligor since financially and legally dependent entities may be subject to same risks.

The type of the obligor strongly affects financial statement and credibility of the obligor. For example, if the obligor is of corporate type, it will have a different financial statement (e.g. asset size) than that of another obligor of type SME. Likewise, a central government could have different credibility than that of a private bank.

*Transaction characteristics*

Characteristics of a transaction are its identity, accounting record, type, nominal amount, return on it, loss from it and its period. Transaction type can be cash credit or non-cash credit. Nominal amount can be written on the transaction contract. Its return can be the interest income accumulated so far over a credit allocation. Period can be the maturity of a credit or a security.

*Credit protection characteristics*

Characteristics of a credit protection are its identity, funding type, protection type, protection amount, and protection period. Various protection types are possible: cash deposit, real estate, credit derivative, guarantee etc. Protection period is the period over which the protection is valid. Provider specifies the third party providing some guarantee for the exposure of the obligor in case of default. It is only applicable for unfunded protections.

Characteristics of the obligor, the transaction and the credit protection can be presented as attributes of data tables to be created for these entities. Each attribute could address some data quality requirements although data quality requirements are not limited to attributes but cover data tables themselves and relationships among those tables.

*Relationship entity for credit risk function*

Credit risk function depends of the attributes of obligors, transactions and credit protections as outlined in Section 3.2.1.1. Therefore, a relationship among those entities should be created in order to quantify credit risk of each transaction belonging to some obligor. Such a relationship entity should consider following aspects:

- Correct matching of the three entities in the resulting table; i.e. pairing transactions of an obligor with its collaterals
- Correct slicing of transactions and credit protections of the obligor during in matching, i.e. multiplication of records for each slice of transaction and credit protection pairs
- Determination of appropriate final risk weight of each slice based on the ratings or risk weights of transaction and credit protection pairs

Thus, the relationship entity for credit risk should contain following attributes:

- Identifiers of obligors, transactions and credit protections
- Final risk weight of the transaction slice
- Exposure amount of the transaction slice before application of credit risk mitigation (CRM) techniques (before the effect of credit protection)
- Risk-weighted exposure amount of the transaction slice after application of CRM techniques (after the effect of credit protection.

#### 3.2.1.2 Identification of Data Sources for Credit Risk Data

Management of the risks that banks are exposed is maintained by risk management departments of banks. Risk management department requires all data relevant to any transaction that bears risk for the bank. Finance and accounting department is primary data source for these transactions since it collects and records data regarding all transactions of various departments such as corporate loans department, personal loans department, treasury department. Information on ratings and collaterals are also critical for risk management functions. IT department provides IT infrastructure for risk management practices. Risk management system is fed by accounting system, rating system, collateral management system, market information system and account management system. IT department provides the infrastructure for the functioning of these systems. Based on this evaluation of data flow to risk management system, viable systems that provide data to risk management system can be identified in a system context diagram given in Figure 6. Information regarding clients are obtained from account management system of the bank. Account information of clients are obtained by account management system. Accounting records regarding transactions or loans of the clients along with accrued interest and commission payments are obtained by accounting system. Accounting properties of transactions such as location in the balance sheet and trial balance are retrieved from accounting systems. Rating system provides credit ratings of obligors (clients) and bailers of the collaterals. Sophistication of the rating system depends on the risk calculation approach used. For example, if the bank uses standard approach for credit risk, rating system generally consists of external ratings given by credit rating agencies. On the other hand, if internal rating is used, then, the system can involve ratings and risk parameters which are derived from statistical models employed within the risk management practices. Collateral management system contains all credit protections provided on behalf of the clients to the bank. The bank uses credit protections both to secure transactions performed with the clients and to mitigate its exposure to risks. The system matches transactions with collaterals provided that their maturities match within some period. Addition or drop of collaterals in matching operations is performed as credit period rolls accordingly. Market information system provides current values of parameters belonging to various markets. For example; exchange rates of currencies, discount rates of securities etc. are fed by this system to the risk management system. The information system lies at the backbone of the systems mentioned. It should provide an IT infrastructure that provides healthy communication, and an interface that enables the roles responsible for risk management to retrieve and aggregate the data in order to use for risk management purposes.

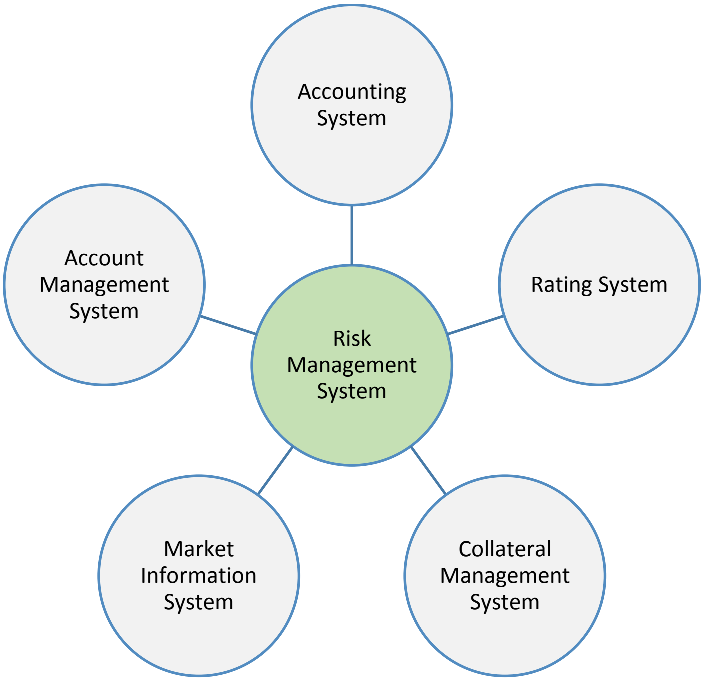

Accounting System
Account Management System
Rating System
Risk Management System
Market Information System
Collateral Management System

**Figure 6** System context diagram proposal for risk management system

### 3.2.1.3 Identification of Data Quality Dimensions for Credit Risk Data

In this section, we will investigate which DQ dimensions are relevant and applicable to the characteristics of obligors, transactions and credit protections. DQ dimensions regarding the business rules due to regulations should be determined in addition those for the attributes of the basic entities themselves. Business rules can be related to the relations among certain attributes of the entities as wells as the relations among entities that enforces referential integrity.

In Section 2.1.2 above we have explored the DQ dimensions that are most frequently referred in the DQA literature. Although credit risk context can cover plenty of DQ dimensions, we will focus on those dimensions which can be quantitatively defined and measured without inference of subjective judgment. These DQ dimensions are uniqueness, completeness, accuracy, consistency and timeliness. Section 2.1.2 also points out that definition of same DQ dimensions may vary from one study to another. Below, we present the particular definitions of DQ dimensions that we adopt in the present study:

***Uniqueness*** refers to having non-duplicate record within a given domain. This dimension can be controlled by inquiring exactly same records within the domain.

***Completeness*** refers to not having null (empty) records within a given domain. This definition is consistent with that presented in Dejaeger et al. (2010) which refers to completeness as the extent of missing and duplicate values. This dimension can be controlled by inquiring null records within the domain.

***Accuracy*** refers to correctness of values within a given domain subject to certain domain constraints. If the values violate those constraints (they could be some range or interval), then accuracy of the domain will be degraded. We refer to the definition of Redman (1996) which is the measure of proximity of data value x to another value x' whose correctness is assumed. Note that we only refer to syntactic accuracy but not semantic accuracy in this context (refer to Section 2.1.2).

***Consistency*** refers to conformance to business rules defined over different domains as well as to referential integrity constraints. Therefore, we are interested in both intra-relational consistency and inter-relational consistency which are referred in Dejaeger et al. (2010) and Batini et al. (2009) (see Section 2.1.2).

***Timeliness*** refers to the definition presented in Dejaeger et al. (2010) as retrieval of recent data upon specific request.

### DQ dimensions for obligors

Identifiers of an obligor such as account number and tax ID do not directly affect risk calculation. However, uniqueness of the obligor is required. An obligor could have different accounts but it should have unique tax ID and client ID. Therefore, **uniqueness** of tax ID or client ID and existence, thus **completeness,** of tax ID, client ID and account number should be ascertained from source data tables. Home country of an entity can be critical for credit rating of the obligor if it is a legal entity rather than a real person. Therefore, **accuracy** and **completeness** of the country should be checked.

Type of the obligor is one of the critical attributes that affect credibility or risk weight. Type set that can be defined for the obligor entity can be created in accordance with the Basel framework which classifies obligors according to their entity type. It can be a central bank, a central government, a bank, a corporate or a SME etc. Their type and their home country play critical role for the credit ratings given by the CRIs. Therefore, **accuracy** and **completeness** dimension of the type of the obligor is crucial for risk management practices.

Financial statement and number of staff of the obligor becomes crucial in determining whether the entity is a corporate or a SME. SMEs are small and medium sized entities whose revenue turnover or balance sheet amount and staff size is under a specified threshold level according to the legislation of the country that bank operates. Therefore, SMEs are subject to different risk weight than corporations. Therefore, **completeness** of those attributes depends on obligor type. It should be controlled accordingly.

Credibility of the obligor is perhaps the most critical attribute for risk calculation. It can be expressed as ratings attributed to the obligor or as risk weights which directly appear in the risk function. If SA is used, then it can be a risk weight. On the other hand, if bank uses IRB approach, then it can demonstrate PD of the obligor. **Completeness** of this attribute depends on the definition of the attribute. It is expressed as risk weight of the obligor or PD of the obligor that is expected to be filled. However, if it is defined as ratings attributed to the obligor; then it may not be forced to be filled since obligors might not be graded by a CRA at all. **Accuracy** and

**completeness** dimensions for credibility attribute of the obligor should be controlled accordingly.

Risk group of the obligor is necessary to identify legally connected obligors (e.g. parents or subsidiaries) which may be exposed to the same risks. If an obligor has no parent or subsidiary entity, then risk group of the obligor is just itself. Therefore, **accuracy** and **completeness** of risk group specification is necessary.

There is relation between obligor type and financial statement and staff size of the obligor. If an obligor is a real person, a central bank or a central government then financial statement and staff size attributes would be irrelevant for that obligor. On the other hand, if the obligor is a corporate or a SME then those attributes should be specified. Moreover, there must be distinction between a corporate and a SME since there are upper threshold values for turnover, asset size and staff size of SMEs. As a result, **consistency** dimension should be considered for the obligor type, turnover, asset size and staff size information for the obligor. Table 5 summarizes DQ dimensions for the attributes of entity of obligors.

**Table 5** DQ dimensions for obligors

| **OBLIGOR** | | | |
|---|---|---|---|
| **Characteristics** | **Attribute** | **Relevant DQ dimensions** | **Original source** |
| Identity | Account number | Completeness | Account Management System |
| Identity | Client ID | Uniqueness, completeness | Account Management System |
| Identity | Tax ID | Uniqueness, completeness | Account Management System |
| Identity | Country | Accuracy, completeness | Account Management System |
| Type | Obligor Type | Accuracy, completeness | Account Management System |
| Financial Statement | Turnover | Consistency | Account Management System |
| Financial Statement | Active size | Consistency | Account Management System |
| Staff Size | Staff Size | Consistency | Account Management System |
| Credibility | Rating/PD | Accuracy, completeness | Rating System |
| Risk Group | Risk Group Code | Accuracy, completeness | Risk Management System |

## DQ dimensions for transactions

An obligor identifier is required to match relevant transaction. **Accuracy** and **completeness** of this attribute must be satisfied.

A transaction must be recorded in accounting sheets. Accounting record specifies the nature of the transaction. **Accuracy** and **completeness** dimensions are needed for the record.

Transaction type can be a cash credit or non-cash credit such as letter of guaranty. It can determine what credit conversion factor (CCF) should be applied. CCF is only applied to non-cash credits. For cash credits, it is applied as 100% by default. CCF changes according to risk level of transaction type for non-cash credits. For SA, CCF values domain set according to the risk level of the transaction are determined in the Basel framework. For IRB approach, CCF values can be calculated internally. **Accuracy** and **completeness** dimensions are required to be used for data quality assessment of transaction type and credit conversion factor.

**Table 6** DQ dimensions for transactions

| **TRANSACTION** | | | |
|---|---|---|---|
| **Characteristics** | **Attribute** | **Relevant DQ dimensions** | **Original source** |
| Credit identity | Transaction ID | Uniqueness, completeness | Accounting System |
| Obligor identity | Account Number | Completeness | Account Management System |
| Transaction record | Accounting record | Accuracy, completeness | Accounting System |
| Type | Transaction type | Accuracy, completeness, consistency | Accounting System |
| Rate | CCF | Accuracy, completeness, consistency | Risk Management System |
| Amount (+) | Principal | Completeness, timeliness | Accounting System |
| Amount (+) | Return | Completeness, timeliness | Accounting System |
| Amount (–) | Provision/Loss | Completeness, timeliness | Accounting System |
| Period | Maturity | Completeness, timeliness | Accounting System |
| Currency Type | Currency Code | Accuracy, completeness | Accounting System |

Amount of the transaction is the direct input in the risk function. Net amount of a transaction consists of principal, return and loss. Depending on the nature of the transaction, there can be return or gain on the transaction such as accrued interest income on a credit provided to an obligor. On the other hand, some provisions might be allocated due to losses or write-offs on a transaction. Therefore, amount, return and loss information for the transaction should satisfy **accuracy** and **completeness** requirements. Depending on reporting frequency, **timeliness** dimension can also be critical for principal, return or loss on the transaction since it can change or accumulate as the period rolls.

Transaction period can be understood as the maturity of the transaction in which the obligation of the obligor proceeds and it poses risk for the bank. A transaction period can be expressed via an opening date and a closing date. The remaining period or maturity is under consideration along with the amount of the transaction and accrued return on the transaction from the point of risk calculation. Therefore; **completeness** and **timeliness** dimensions are significant for the period of transaction.

Accounting record of a transaction is determiner of the type of the transaction. Since two attributes are correlated, **consistency** rules must be enforced. Similarly, transaction type specifies what CCF should be applied. Therefore, consistency dimension should be included in DQ assessment for those two attributes either.

Currency type of the transaction should satisfy **accuracy** and **completeness** dimensions. Table 6 summarizes DQ dimensions for the attributes of entity of transactions.

## DQ dimensions for credit protections

Type of credit protection determines the effect of the protection on the transaction. Protection type can be cash deposit, security, real estate, guarantee etc. Therefore, **accuracy** and **completeness** of the protection is important. If credit protection is by a guarantee then its provider and the credibility or risk weight of the provider should be demonstrated. If credit protection is by some type other than a guarantee then risk weight of the protecting asset should be demonstrated.

**Table 7** DQ dimensions for credit protections

| **CREDIT PROTECTION** | | | |
|---|---|---|---|
| **Characteristics** | **Attribute** | **Relevant DQ dimensions** | **Original source** |
| Protection Identity | C. Protection ID | Uniqueness, completeness | Collateral Management System |
| Type | Protection Type | Accuracy, completeness | Collateral Management System |
| Credibility | Provider Rating/PD | Accuracy, completeness | Rating System |
| Amount | Value | Completeness, timeliness | Collateral Management System |
| Period | Maturity | Completeness, timeliness | Collateral Management System |
| Currency Type | Currency Code | Accuracy, completeness | Collateral Management System |

Protection amount is important for risk function since it will reduce exposure of the transaction protected. Therefore, **completeness** and **timeliness** dimensions should be in concern.

Protection period should be known for certain in order to use the protection in the risk mitigation practices. Similar to the period of transaction, the remaining maturity is of concern. Mismatch between remaining maturities of the transaction and the credit protection, i.e. if maturity of the protection is earlier than that of the transaction, this poses certain risk and changes the nature of calculation. Due to such reasons, **completeness** and **timeliness** of this attribute should be satisfied.

Provider credibility is subject to risk calculation if the protection is by a guarantee. In that case, risk weight or PD of the protection provider (depending on calculation approach) appears in the risk function. Therefore, **accuracy** and **completeness** dimensions are required for this attribute.

Currency type of the protection should satisfy **accuracy** and **completeness** dimensions. Table 7 summarizes DQ dimensions for the attributes of entity of credit protections.

**DQ dimensions for credit risk function**

Since credit risk entity results from the relationship among the three root entities, the attributes of credit are borrowed or derived from the other three entities. Borrowed attributes are identifiers of the other entities while derived attributes are the resulting attributes of relationship among the entities. Therefore, this entity should meet the requirements for referential integrity as well as consistency conditions.

**Table 8** DQ dimensions for relations among the entities

| **CREDIT RISK FUNCTION** | | | |
|---|---|---|---|
| **Characteristics** | **Attribute** | **Relevant DQ dimensions** | **Original source** |
| Obligor Entity | Client ID | Completeness, consistency | Account Management System |
| Credit identity | Credit Number | Completeness, consistency | Accounting System |
| Protection Identity | C. Protection ID | Completeness, consistency | Collateral Management System |
| Credibility | Final Rating (or Final Risk Weight) | Accuracy, completeness, consistency | Risk Management System |
| Amount | Exposure Before CRM (slice) | Completeness, consistency | Risk Management System |
| Amount | Credit Protection Allocation (slice) | Completeness, consistency | Risk Management System |
| Amount | RWA After CRM (slice) | Completeness, consistency | Risk Management System |

Obligor identity, transaction identity and credit protection identity for a certain event in credit risk entity should be consistent with those in the other entities. Therefore, **consistency** dimension is required for these attributes.

Due to possible slicing of transaction amount for the purposes of application CRM, a transaction can be divided to several records. Therefore, total amount of slices existing in credit risk entity should **consistently** match to the amount belonging to that transaction existing root transaction entity.

A protection may not be completely used in risk mitigation. In fact, a credit protection can be used for more than one transaction if it suffices. In other cases, a protection may not be wholly used for a transaction due to legal restrictions. Therefore, use amount of a credit protection for a transaction slice should be specified for risk mitigation purposes. Coverage amount of the protection should not exceed the limits set due to reasons mentioned above. Therefore, **consistency** dimension should be in consideration for the attribute referring to allocation amount of protection.

Final risk weight of a transaction slice is determined by the results of matching the transaction slice to a corresponding credit protection slice. Risk weights of either transaction or credit protection will be the final risk weight depending on whether the protection slice covers the transaction slice or not. Therefore, final risk weight of a slice should be **consistent** with the risk weights of the transaction slice and the protection slice.

Risk weighted exposure amount after the effect of CRM techniques should be **consistent** with final risk weight, exposure before CRM and amount of protection allocation since it is resulting attribute of those attributes. Table 8 shows DQ dimensions for the attributes of credit risk entity.

### 3.2.2 Phase 2: Measurement of Data Quality

Data quality dimensions that are relevant to credit risk context are defined in Section 3.2.1.3. These DQ dimensions are determined to be uniqueness, accuracy, completeness, timeliness and consistency. Measurement of data quality of credit risk requires that DQ metrics be developed. These metrics should be based on DQ dimension defined in the definition phase. In this section, we are going to develop DQ metrics based on DQ dimensions defined in order to assess data quality of credit risk.

#### 3.2.2.1 Metrics for DQ dimensions

Metrics are used to present the results of undesired outcomes for a given DQ dimension. After calculating the metrics for each attribute for a given DQ dimension, the results will be transformed to data quality performance scores in order to perform DQA. DQ metrics defined in the present study are actually ratios. That is, they refer to ratio of the number of undesired outcomes to the number of total outcomes. Therefore, observation of non-zero values as a result of measurement of the metrics points out existence of a DQ issue.

General forms of the DQ metrics developed for the DQ dimensions used in the present study are provided in Table 9. Also, detailed descriptions of the DQ metrics for each attribute of the entities for the given DQ dimensions are given in this section.

**Table 9** General forms of the DQ metrics developed for the DQ dimensions

| **DQ Dimension** | **General Metric Form** |
|---|---|
| *Uniqueness* | Total number of records in a table that has duplicate records for certain FIELD that must be unique to total number of all records in the table |
| *Accuracy* | Total number of records in a table whose certain FIELD violates domain constraints of that field to total number of all records in the table |
| *Completeness* | Total number of records in a table whose certain FIELD that must be non-null is null to total number of all records in the table |
| *Consistency* | Total number of records in a table whose certain FIELD value contradicts with the value(s) of other dependent fields(s) to total number of all records in the table |
| *Timeliness* | Total number of records in a table whose certain FIELD was updated before date DD.MM.YYYY to total number of all records in the table |

**Metrics for uniqueness**

Uniqueness of an entity can be provided by the identifier of that entity. Obligor identification can be ensured via tax ID, social security number (SSN) or citizenship number. In addition, client ID which is defined by the bank can be used to identify the obligor. A bank may use any of these identifiers to trace the obligor. Similarly, uniqueness of transactions and credit protections in their root tables can be provided by assignment of IDs to those entities by the corresponding original data source.

Performance metrics for uniqueness of the attributes of obligors are defined as follows:

- Total number of records in obligors table that have duplicate records for tax ID to total number of all records in the table.
- Total number of records in obligors table that have duplicate records for client ID to total number of all records in the table.

Performance metrics for uniqueness of the attributes of transactions can be defined as follows:

- Total number of records in transactions table that have duplicate records for transaction ID to total number of all records in the table.

Performance metrics for uniqueness of the attributes of credit protections can be defined as follows:

- Total number of records in credit protections table that have duplicate records for credit protection ID to total number of all records in the table.

If any one of these metrics has a non-zero value, this issue must be handled in database application via definition of unique fields which are primary keys.

### Metrics for accuracy

Accuracy can be interpreted in different manners according to its definition as discussed in Section 2.1.2. Originality of each attribute value in terms of its original source and its proximity to its original value should be assessed for data quality assessment purposes. This can lead to the definition of various metrics for this dimension. However, we are going to focus solely on the attributes whose values should lie within a domain.

Performance metrics for accuracy of the attributes of obligors are defined as follows:

- Total number of records in obligors table whose country is not in the country domain set, $D_{country}$ (domain set can be expressed as country codes, e.g. TR, US etc.) to total number of all records in the table.
- Total number of records in obligors table whose type is not in the obligor type domain set, $D_{otype}$ (domain set contains entity types according to the Basel framework, e.g. central bank, central government, corporate, SME, individual person etc.) to total number of all records in the table.
- Total number of records in obligors table whose rating does not exist in the rating domain set, $D_{orating}$ (domain set can be expressed as credit quality level, e.g. 1, 2, 3 etc. or as grades AAA+, AA-, BBB+ etc. or as PD rates) to total number of all records in the table.

Performance metrics for accuracy of the attributes of transactions are defined as follows:

- Total number of records in transactions table whose accounting record violates the constraints imposed on accounting sheets by regulations to total number of all records in the table (for example; entry number of a transaction may not belong to accounting record set at all due to operational errors).
- Total number of records in transactions table whose type is not in the transaction type domain set, $D_{ttype}$ (domain set contains transaction types according to the Basel framework, e.g. cash credits, cash credits from participation funds, non-cash credits with lowest risks, non-cash credits with highest risks etc.) to total number of all records in the table.
- Total number of records in transactions table whose CCF is not in the CCF interval (this is the case when IRB approach is used, e.g. [%0, %100]) or domain set, $D_{CCF}$ (this is the case when SA is used, e.g. %0, % 20, %50 or %100 are used according to level of riskiness of the credit) to total number of all records in the table.
- Total number of records in transactions table whose currency type is not in the currency type domain set, $D_{currency}$ (domain set can be expressed as currency codes, e.g. TRY, USD etc.) to total number of all records in the table.

Performance metrics for accuracy of the attributes of credit protections are defined as follows:

- Total number of records in credit protections table whose type is not in the protection type domain set, $D_{ptype}$ (domain set contains protection types according to the Basel framework, e.g. cash deposits, security, real estate, guarantee etc.) to total number of all credit records in the table.

- Total number of records in credit protections table whose rating does not exist in the rating domain set, $D_{prating}$ (domain set can be expressed as credit quality level, e.g. 1, 2, 3 etc. or as grades AAA+, AA-, BBB+ etc. or as PD rates) to total number of all records in the table.
- Total number of all records in credit protections table whose currency type is not in the currency type domain set, $D_{currency}$ (domain set can be expressed as currency codes, e.g. TRY, USD etc.) to total number of all records in the table.

Performance metrics for accuracy of the attributes of credit risk entity are defined as follows:

- Total number of records in credit risk table whose final rating (or risk weight) does not exist in the rating domain set, $D_{CRrating}$ (domain set can be expressed as credit quality level, e.g. 1, 2, 3 etc. or as grades AAA+, AA-, BBB+ etc. or as PD rates) to total number of all records in the table.

**Metrics for completeness**

Attributes that require to be filled are addressed by completeness dimension. It refers to inspection of null values for a given attribute. An attribute value can be null due to two reasons. One is that it is not required for all cases of the attribute. The other is due to missing values which should be filled somehow. Completeness dimension addresses missing values which are required to be filled. The other aspect is addressed by the consistency dimension, i.e. determination of whether an attribute is to be null or not under certain conditions.

Performance metrics for completeness of the attributes of obligors are defined as follows:

- Total number of records in obligors table whose account number is null to total number of all records in the table.
- Total number of records in obligors table whose tax ID is null to total number of all records in the table.
- Total number of records in obligors table whose country is null to total number of all records in the table.
- Total number of records in obligors table whose obligor type is null to total number of all records in the table.
- Total number of records in obligors table whose rating/PD/risk weight is null to total number of all records in the table.

Performance metrics for completeness of the attributes of transactions are defined as follows:

- Total number of records in transactions table whose transaction number is null to total number of all records in the table.
- Total number of records in transactions table whose account number is null to total number of all records in the table.
- Total number of records in transactions table whose accounting record is null to total number of all records in the table.
- Total number of records in transactions table whose CCF is null to total number of all records in the table.

- Total number of records in transactions table whose principal amount is null to total number of all records in the table.
- Total number of records in transactions table whose return amount is null to total number of all records in the table.
- Total number of records in transactions table whose provision/loss amount is null to total number of all records in the table.
- Total number of records in transactions table whose maturity is null to total number of all records in the table.
- Total number of records in transactions table whose currency code is null to total number of all records in the table.

Performance metrics for completeness of the attributes of credit protections are defined as follows:

- Total number of records in credit protections table whose credit protection ID is null to total number of all records in the table.
- Total number of records in credit protections table whose protection type is null to total number of all records in the table.
- Total number of records in credit protections table whose provider is null to total number of all records in the table.
- Total number of records in credit protections table whose rating/PD is null to total number of all records in the table.
- Total number of records in credit protections table whose value is null to total number of all records in the table.
- Total number of records in credit protections table whose maturity is null to total number of all records in the table.
- Total number of records in credit protections table whose currency code is null to total number of all records in the table.

Performance metrics for completeness of the attributes of credit risk are defined as follows:

- Total number of records in credit risk table whose obligor ID is null to total number of all records in the table.
- Total number of records in credit risk table whose transaction ID is null to total number of all records in the table.
- Total number of records in credit risk table whose credit protection ID is null to total number of all records in the table.
- Total number of records in credit risk table whose final rating is null to total number of all records in the table.
- Total number of records in credit risk table whose exposure before CRM is null to total number of all records in the table.
- Total number of records in credit risk table whose amount of credit protection allocation is null to total number of all records in the table.
- Total number of records in credit risk table whose risk-weighted exposure after CRM is null to total number of all records in the table.

**Metrics for consistency**

Consistency dimension is required in order to control validity of business rules among certain attributes. It can also be used to check referential integrity among the entities. The rules under the Basel framework can drive such business rules in the context of credit risk.

Performance metrics for consistency of the attributes of obligors can be defined as follows:

- Total number of records in obligors table whose obligor type is SME or corporate but turnover and active size information is null to total number of all records in the table (at least one of turnover or active size information is sufficient).
- Total number of records in obligors table whose obligor type is SME or corporate but staff size information is null to total number of all records in the table.
- Total number of records in obligors table whose obligor type is SME but both turnover value and active size value is greater than threshold value (e.g. 40 million TL) to total number of all records in the table (at least one of turnover or asset size values smaller than threshold value is sufficient).

Performance metrics for consistency of the attributes of transactions can be defined as follows:

- Total number of records in transactions table whose accounting record number is X but transaction type is T' instead of T to total number of all records in the table (under the assumption that record X implies type T).
- Total number of records in transactions table whose transaction type T but CCF applied is F' instead of F to total number of all records in the table (under the assumption that type T implies use of CCF F).

Performance metrics for consistency of the attributes of credit risk entity can be defined as follows:

- Total number of records in credit risk table whose obligor ID does not exist at obligor table to total number of all records in the table (referential integrity constraint – determination of non-existent obligors).
- Total number of records in credit risk table whose transaction ID does not exist at transactions table to total number of all records in the table (referential integrity constraint – determination of non-existent transactions).
- Total number of records in credit risk table whose credit protection ID does not exist at credit protections table to total number of all records in the table (referential integrity constraint – determination of non-existent credit protections).
- Total number of records in credit risk table to which some credit protection allocated but their final ratings do not match with those of the protection, or to which no credit protection allocated at all but their final ratings do not match with those of the obligor to total number of all records in the table.
- Total number of transactions in credit risk table whose total slice amounts do not add up to those of corresponding transactions in transaction table to total number of transactions in the table.
- Total number of credit protections in credit risk table whose total slice amounts are greater than those of corresponding credit protections in credit protections table to total number of credit protections in the table.

- Total number of records in credit risk table whose risk-weighted exposure amounts after CRM for transaction slices do not equal to the multiplication of exposure amount before CRM by final risk weight of the slices to total number of all records in the table.

**Metrics for timeliness**

How recent a value of an attribute is required in the context of credit risk reporting determines the significance of timeliness dimension of the attribute. Risk reporting frequency may change depending on the nature and type of the transaction. However, monthly reporting period is commonly used for credit risk reporting. Therefore, certain attribute values are required to be updated at least monthly. Especially, attributes related to amount may change due to change of exchange rates or due to accumulation on return or loss.

Performance metrics for timeliness of the attributes of transactions can be defined as follows:

- Total number of records whose principal amount value was updated before date DD.MM.YYYY to total number of all records in the table.
- Total number of records whose return amount value was updated before date DD.MM.YYYY to total number of all records in the table.
- Total number of records whose loss amount value was updated before date DD.MM.YYYY to total number of all records in the table.
- Total number of records whose maturity information was updated before date DD.MM.YYYY to total number of all records in the table.

Performance metrics for timeliness of the attributes of collaterals can be defined as follows:

- Total number of records whose fair value was updated before date DD.MM.YYYY to total number of all records in the table.
- Total number of records whose maturity information was updated before date DD.MM.YYYY to total number of all records in the table.

#### 3.2.2.2 DQA methods for DQ metrics

There are various DQA methods described in the literature. Borek et al. (2011) has classified such methods that are used to assess data quality in certain contexts. These methods can be applied to various DQ problems. DQ methods presented in that study are summarized in Table 10.

Column analysis, cross-domain analysis, data validation, domain analysis, matching algorithms, PK/FK analysis, schema matching and semantic profiling can be used in order to measure performance metrics defined in Section 3.2.2.1. Lexical analysis which is used to map unstructured data to structured set of attributes is, on the other hand, hardly used in DQA since credit risk data usually are of structured type.

**Table 10** DQ assessment methods (Borek et al., 2011).

| **DQA Method** | **Description** |
|---|---|
| Column Analysis | Computation related to uniqueness, null values, min and max value, totals, standard deviations, inferred types etc. in a column |
| Cross-domain Analysis | a.k.a. functional dependency analysis, identification of redundant data across columns in the same or different tables |
| Data Validation | Verification of values against a reference data set via algorithms |
| Domain Analysis | Checking if a data value within certain domain of values |
| Lexical Analysis | Mapping unstructured content to structured set of attributes, usually applied to STRING columns, use of rule-based & supervised-model based techniques |
| Matching Algorithms | a.k.a. record-linkage algorithms, identification of duplicates, "Sorted Neighborhood Method (SNM)" used to reduce runtime of matching |
| Primary Key / Foreign Key Analysis | Analysis applied to columns from different tables to detect good candidates for Primary Key /Foreign Key relation |
| Schema Matching | Detection of semantically equivalent attributes via algorithms (schema-based matchers, instance-level matchers, hybrid approaches) |
| Semantic Profiling | Business rules on data (in columns or tables) and measurement of the compliance of data to the rules |

**Column analysis** is usually applied in order to produce outcomes related to total, max, min etc. operations. Statistical operations such as standard deviation can also be applied via column analysis. It can be used to extract basic simple outcomes concerning the column or attribute itself. Therefore, column analysis can be used to assess uniqueness and/or completeness of the relevant attributes determined in Section 3.2.1.3.

Although it is not directly referred in this study, identification of redundant data is significant for effective data quality assessment for credit risk context. While discussing data taxonomies in Section 3.2.1.1 and relevant data sources in Section 3.2.1.2, we point out separation of various systems which provide different data types for risk management system. Building data taxonomy in accordance with the business rules implied and compelled by the Basel framework and extracting various data content from different data sources brings the issue of redundant data along with the issue of consistency due to concern for referential integrity. Therefore, **cross-domain analysis** can be used to detect such redundant data. Banks may face problems in normalization of various data types in their database applications which may cause redundancy and referential integrity problems. Therefore, cross-domain analysis could be beneficial and good starting point to detect and solve such issues.

**Data validation** method can also be used in comparison of original data sources with the final data used for risk measurement purposes. Determination and traceability of reference data set is critical for data validation. Identification of data sources as mentioned in Section 3.2.1.2 is key step in data validation.

**Domain analysis** can be used to check violation of domain set constraints. Accuracy dimension relevant to certain attributes points out detection of such violations.

Domain analysis can be realized against pre-defined set of values or some range of values.

**Matching algorithms** can be used to detect duplicate records relevant to an entity that should contain unique records. Uniqueness dimension of an attribute is relevant for matching algorithms.

**Primary Key / Foreign Key (PK/FK) analysis** can be used to analyze certain attributes belonging to the entities of credit risk data that might be good candidates to be primary key or foreign key. Considering the entities of obligors, transactions and credit protections, identifier attributes can be analyzed for PK/FK relationship. This analysis can have substantial effect on creating relationship tables from the three entities in order to quantify and measure individual and overall risks of transactions.

**Schema matching** can be beneficial for certain attributes of the credit risk entities. For example, rating grades given by different CRIs can be semantically matched (e.g. BBB+ grade given by S&P is equivalent to Baa1 grade given by Moody's).

**Semantic profiling** can be used to check consistency among attributes or entities required by the business rules. Consistency dimension of certain attributes explored and defined in Section 3.2.1.3 can be controlled and assessed via semantic profiling.

#### 3.2.2.3 Key Quality Performance Indicators (KQPIs) and Composite Quality Performance Indicators (CQPIs)

We have developed metrics for data quality assessment of credit risk above in Section 3.2.2.1. These metrics are based on the attributes and relations of three entities, i.e. obligors, transactions and credit protections. In order to create healthy and effective relationship tables that can be used for risk quantification and aggregation, these metrics should provide acceptable results in terms of data quality aspects of the attributes defined. Metrics developed in Section 3.2.2.1 are limited to assessment of several DQ dimensions which are accuracy, completeness, uniqueness and consistency. The metrics evaluate total occurrences or violations confronted out of total outcomes or records relevant to a certain entity table. One should expect those ratios to be close to zero or null to ensure satisfaction of data quality requirements of relevant attributes and entities. DQ metrics developed to calculate violation rate of each attribute relevant to a given DQ dimension can be transformed to quality performance indicators in order to standardize the results of DQA. Two types of quality performance indicators can be defined: individual indicators and composite indicators. We have developed such indicators in the present study for the purposes of the assessment of the results of DQ metrics more meaningfully.

Individual quality performance indicators are developed in the present study by transforming DQ metrics to certain value. Each individual indicator corresponds to a DQ metric developed. Since observation of higher amount of violations means higher DQ metric value, transformation function will consider non-violations in order to state that higher indicator value means better performance. Hence, the transformation function for an individual indicator can be defined as follows:

$$KQPI_{i,d} = T\left(DQM_{i,d}\right) = 100 \times (1 - DQM_{i,d})/N$$

where key quality performance indicator *i* (*$KQPI_{i,d}$*) denotes individual indicator *i* for metric *i* for given dimension *d*, *$DQM_{i,d}$* denotes observed value of DQ metric *i* for given dimension *d*, *T(.)* denotes transformation function, and *N* denotes upper bound for *$KQPI_{i,d}$* scale ranging from 0 to *N* ($N > 0$). Value of *N* corresponds to upper bound (the best performance value) while value of zero corresponds to lower bound (the worst performance value) in the indicator scale. Thus, the KQPI result will be "*n*" such that *n* will be between 0 and N ($0 \leq n \leq N$).

Weights for each KQPI can be determined according to the significance of the field for credit risk measurement and calculation. CQPI for each dimension can be constructed by summing up weighted KQPIs where sum of weights add up to one. Weights of KQPI to form CQPI are determined based on various cases. One case could be treating all fields in concern equally. Another case could be giving higher significance, so higher weights, to the fields directly affecting calculation of credit risk exposure than the other remaining fields. Furthermore, data fields can be clustered according to their significance in a way that fields existing in same clusters have same weights.

Table 11 illustrates how data fields can be grouped. Another alternative case for determination of risk weights could be based on changes in the functions of credit risk management. In other words, the weight could be dynamic.

**Table 11** Clustering data fields of credit risk tables according to their significance for credit risk calculation

| **Cluster Description** | **Data fields in the cluster** | **Weight for the cluster** |
|---|---|---|
| Cluster A: Fields directly represented as parameters in credit risk function | Field(a1), Field(a2), … , Field(aN) | $W_a$ |
| Cluster B: Fields affecting parameters in credit risk function | Field(b1), Field(b2), … , Field(bM) | $W_b$ |
| Cluster C: Fields not having significant effect on credit risk calculation | Field(c1), Field(c2), … , Field(cK) | $W_c$ |
| $W_a > W_b > W_c$ | | |

We know that each KQPI developed by standardization of a DQ metric value represents the performance of a relevant attribute for a given DQ dimension. Composite indicators can be constituted by combination of weighted KQPIs for each DQ dimension. Weights of each KQPI to form a composite indicator can be determined either equally for each KQPI or according to criticality of the attribute for risk quantification and calculation, i.e. its factor effect in risk function. If we denote *$KQPI_{i,d}$* as key quality performance indicator for metric *i* given DQ dimension *d* and further denote *$CQPI_d$* a composite quality performance indicator for DQ dimension *d*, then *$CQPI_d$* can be defined as follows:

$$CQPI_d = \sum_i w_{i,d} \times KQPI_{i,d}$$

$W_i$ is the weight of each KQPI satisfying $\sum_i w_{i,d} = 1$ for each d.

Threshold values for CQPIs can be defined in order to make overall assessment. They can be specified for each CQPI according to acceptable occurrence rates. Data quality of and attribute for a specific DQ dimension can be evaluated by these thresholds. Data quality can be classified as of very high quality, high quality, medium quality, low quality and very low quality. Quality range can be more diversified according to the criticality of the assessment. Data quality assessment for a certain DQ dimension can be performed as follows:

$$DQA_d = \begin{cases} Very\ low\ quality, & CQPI_d < T_1 \\ Low\ quality, & T_1 \leq CQPI_d < T_2 \\ Medium\ quality, & T_2 \leq CQPI_d < T_3 \\ High\ quality, & T_3 \leq CQPI_d < T_4 \\ Very\ high\ quality, & T_4 \leq CQPI_d \end{cases}$$

*$DQA_d$* denotes data quality assessment results for a given DQ dimension while $T_1$, $T_2$, $T_3$ and $T_4$ denote threshold values based on desirable data quality levels for a bank. Different threshold levels can be determined for different DQ dimensions depending on criticality attributed to type of DQ dimension.

### 3.2.3 Phase 3: Analysis of data quality

Based on data quality assessment results obtained from evaluation of metrics, analysis of data quality can be performed in order to investigate underlying causes of data quality issues. DQ issues may arise in local areas or it can be structural ones (e.g. issues related to IT infrastructure, issues related to data architecture etc.)

Generally speaking, data quality problems are the result of lack of effective data management. As the complexity of data collected increases, data management capabilities of banks could face difficulties leading to increase in risk of poor data quality. There could be various reasons of poor data quality. Lee et al. (2006) states common DQ challenges as multiple data sources, subjective assessment in data production, security/accessibility trade-off and changing data requirements. Moges et al. (2011 and 2013) and Moges (2014) revealed that inconsistency and diversity of data sources are the overwhelming recurring challenges of data quality of credit risk as a result of number of surveys conducted to financial institutions. Problems related to data collection process which involves manual data entry processes are also found to be one of the significant reason for poor DQ by the study. Borek et al. (2011) classified DQ related problems in a systematic way. The study classifies fundamental DQ problems in a two by two matrix. While one dimension groups the problems in terms of context dependency, the other dimension groups them in terms of either data or user perspectives.

Results and evaluation of quality performance metrics defined in Phase 2 on credit risk data could imply underlying DQ challenges. We are going to explore possible DQ challenges for those metrics defined based on DQ dimensions of accuracy, completeness, uniqueness, consistency and timeliness. Poor quality performance in each DQ dimension implies existence of certain DQ problems.

**Problems related to uniqueness dimension**

Duplicate records observed in a field which should be unique are regarded as violation of uniqueness. Uniqueness of an attribute or a record can be violated due to various reasons. Manual entry of records, uncontrolled consolidation of tables, and use of multiple data sources carrying same data could be reasons of such violations. If tables used in risk management system are created and filled manually then errors made by data operators during manual entry process might be cause of duplicates. If obligor identifiers such as tax ID or client ID in obligors table is duplicated then there are problems in identification of primary keys. If PK/FK analysis for data tables of credit risk is not properly performed, such problematic issues could easily arise, lead to violation of uniqueness and produce duplicates. On the other hand, if data tables used in risk management system are fed automatically by other systems mentioned in Section 3.2.1.3, then, one may suspect from reproduction of a record from different tables. If records are replicated from fragmented data tables located in other systems, due to poor management on data consolidation could trigger such problems. When violation of uniqueness condition for a certain attribute such as tax ID of an obligor is detected, the record should be traced to its original source. For example the process of obtaining tax ID from account management system should be monitored until the final obligors table is used by risk management system. Column analysis can be beneficial in initial detection of such anomalies.

**Problems related to completeness dimension**

Undesired null values in fields which should be full are regarded as violation of completeness. Inability to satisfy completeness requirements of certain attributes could also be caused by similar reasons that can be faced due to the difficulty of guaranteeing uniqueness of an attribute. Manual entry of records, ETL problems during automatic filling and communication problems among systems may cause violation of completeness for certain fields. If data is inserted manually in the final tables used by risk management system, errors during manual entry by data operators could cause incompleteness of certain fields. Also, even if the process is automated, some systematic error in extracting the data from another data source could still prevent filling some fields. Results of performance metrics for different attributes can contribute to detect underlying causes of the problem. Use of multiple data sources which have incompatibilities among them may cause mismatch of data values ultimately distorting completeness of information.

**Problems related to accuracy dimension**

Fields containing inaccurate values, i.e. violation of domain constraints can be regarded as violation of accuracy of data. Accuracy of an attribute, a field or a record can be distorted by several reasons. Manual entry of records, lack of controls on domain constraints (data validation analysis), use of unstructured data sources, ETL problems during transformation of original data may cause such violations. In addition, use of multiple data sources for extraction same data can cause inconsistencies. Moges et al. (2011 and 2013) and Moges (2014) stress that the diversity of data sources may cause mismatches since they may not be updated or changed simultaneously. This can cause inconsistency of final data with original data sources. Data validation algorithms can be used to inspect authenticity of data against the reference data set. Determination of reference data set is critical in this regard.

Accuracy problems due to violation of domain constraints can be traced via domain analysis.

**Problems related to consistency dimension**

Inconsistencies observed among dependent fields can be regarded as violation of consistency of data. DQ problems stated for accuracy dimension are also valid for consistency dimension. Manual entry of records, use of multiple data sources carrying same data, uncontrolled consolidation of tables, erroneous definition of business rules, incapability of effective and adequate definition of data table schemas, and failure to relate dependent fields to each other can be causes of such violations. Inconsistencies among different data sources can distort consistency dimension of an attribute. Consistency among different attributes could stem from poor consolidation of original or temporary data tables which have different schema. Lack in enforcement of business rules among various attributes consolidated from different data tables could yield such anomalies. Application of schema matching and semantic profiling can contribute to explore DQ issues concerning consistency dimension.

**Problems related to timeliness dimension**

Problems revealed by the metrics defined for timeliness dimension can be caused by manual update or change of data whose timeliness is critical for credit risk management. If periodic update or change of final tables is not automatized, the risk for miscalculation of risk items may increase. Other problems could be systematic problems in automatized processes preventing timely update of data from other data sources.

### 3.2.4 Phase 4: Improvement of data quality

Improvement of data quality of credit risk can be motivated by DQ problems analyzed at phase 3. The criticality and severity of the underlying DQ problems will determine the extent and urgency of improvement phase. Proposal for improvement action can range from utilization of several improvement techniques on existing data management system or information system to development of a totally new system consisting of new infrastructure and data taxonomies. There is limited concern on detailed exploration of improvement techniques and practical application of them for data quality assessment in the literature. TDQM approach stresses the need for identification of key areas for improvement such as alignment of information flow and work flow with the corresponding information manufacturing system, and realignment of the key characteristics of the information product with business needs. Bonollo and Neri (2011) propose best practice methods based on centralized approach to risk data with silo organizations involving integration of financial data and risk data.

Improvement of data quality of credit risk data should cover both context-dependent and context-independent requirements for data quality. Context-independent requirements for data quality refer to the capability of banking system providing a sound infrastructure and data governance for risk management system no matter the content of data. Disintegration of systems according to their specific functions along with convenient consolidation of data extracted from these systems for risk management purposes is key for satisfaction of context-independent requirements for data quality. Context-dependent requirements for data quality refers to developing well-established data taxonomies in accordance with business rules, i.e. rules enforced by the Basel framework, and data tables which are convenient for building efficient relationships among them in order to quantify credit risk accurately and effectively. DQ problems revealed at Phase 3 are key to investigate possible improvement areas. That is, comprehensive analysis of the causes of DQ issues contributes to identification of areas which should be improved.

If DQ problems stem from multiple data sources, linkages to these data sources and existence of control points should be inspected. The possibility of consolidation of different data sources providing same data should be investigated. This investigation should include handling data inconsistencies and analysis of loss of data due to consolidation.

DQ problems caused by manual errors should be analyzed by investigation of roles and responsibilities of data operators. Identification of user roles/domains prone-to-error is critical to reduce those errors. Such errors can be eliminated by reduction of manual workarounds and increase of automatized operations. In addition, data operations procedures might be updated.

DQ problems stem from the process of ETL should be inquired by analyzing the steps of the process. Examination of those steps which are data collection (extraction), transformation of original data to credit risk data, and transferring data transformed to credit risk management system (load) will reveal weak areas of the process that need to be improved.

DQ problems originated from inconsistencies among fields correlated to each other due to erroneous definition of business rules can be worked out by redesigning data tables with their attributes and relationships among these tables.

Analysis of those DQ issues will contribute to develop alternative set of solutions for the areas in which DQ level should be improved. The solution set may range from short-term and cost-effective solutions to long-term and expensive solutions. Short-term solutions for improvement of DQ level can involve rapid changes or modifications to the system while long-term solutions may require IT investment involving development of a new IT infrastructure and data architecture. Selection among several alternatives depends on the criticality and urgency of DQ issues and strategic and economic impact of them on the bank’s business. Cost-benefit analysis of each viable alternative will contribute to selection of feasible and effective solutions to resolve DQ issues confronted and to improve DQ level in those areas where such issues emerge.

# CHAPTER 4

# IMPLEMENTATION AND RESULTS

Chapter 3 elaborated on the method for applying TDQM for bank credit risk data from an IS perspective. The present chapter is devoted to the implementation of TDQM phases identified in Chapter 3 for the specific case of the Turkish banking sector. First, templates prepared for credit risk data by Turkish banking supervision authority, BRSA, are discussed in terms of their eligibility for DQ and IT requirements. Since these templates are used by banks to consolidate and present their credit risk data, their conformance to database normalization rules are critical for DQA. Then, credit risk data of a specific bank (ABC Bank, see Section 4.2) belonging to a specific period (month) which is consolidated using the templates provided by BRSA is assessed in terms of its DQ. Assessment is based on the TDQM phases identified in Chapter 3. Then, results of DQA are presented. Since the author of the present study has been a member of the team of auditors for ABC Bank, the proposed method has been applied in the audit process applied during the period April 2015 – May 2015 in order to identify major DQ problems causing deficiencies in credit risk management. An action plan (see Section 4.2.4) based on the ensuing audit report dated May 2015 has been prepared by ABC officers in order to resolve the findings in the report.

## 4.1 Evaluation Credit Risk Data Forms

### 4.1.1 Content of Data Forms

BRSA has prepared four database tables in late 2013 so that banks report their credit risk data on individual obligor and transaction basis. These tables are only used for reporting credit risk under SA since no bank has been authorized to adopt and use IRB approach due to the fact that the preparation of concerning regulation was not completed yet by the end of July 2015. The aim for preparation and enforcement of these data tables for SA was to standardize data format so as to minimize reporting errors. The data forms are used during both on-site and off-site audits. Data tables are titled as clients, credits, collateral, and repo and reverse repo transactions. The critical data tables are clients, credits and collaterals. Repo and reverse repo transactions are reported in a different table due to their specific nature although they are certain type of credits or transactions. The scope of this study will cover clients, credits and collaterals. Fields of these tables are given in Table 12, Table 13 and Table 14.

Clients table contains information belonging to clients of the bank who have transactions with the bank. Information regarding legal identity and location of the client, financial statement if it is a firm, and risk category and risk weight of the client are provided in this table.

**Table 12** Clients table and its fields

| **CLIENTS** | | |
|---|---|---|
| **Field Name** | **Data Type** | **Description** |
| Client ID | Number | Client ID given by the bank |
| Tax ID | Number | Tax ID or citizenship ID of the client |
| Client Name | Text | Name of the client (real person or legal entity) |
| Risk Category Code | Text | Risk category code of the client |
| Risk Category Name | Text | Risk category name of the client |
| Country Code | Text | Country code where the client resides |
| Client Risk Class | Text | Risk class of the client according to the regulation |
| Firm Turnover | Currency | Revenue amount if the client is a company |
| Firm Staff Size | Number | Staff size if the client is a company |
| Firm Asset Size | Currency | Active size amount if the client is a company |
| Firm Segment | Text | Segment (SME or corporate) if the client is a company |

**Table 13** Credits table and its fields

| **CREDITS** | | |
|---|---|---|
| **Field Name** | **Data Type** | **Description** |
| Client ID | Number | Client ID given by the bank |
| Tax ID | Number | Tax ID or citizenship ID of the client |
| Trial Balance Code | Text | Trial balance record number of the credit |
| Credit Account No | Text | Credit account number allocated to the client |
| ISIN Code | Text | Unique ISIN codes of the securities |
| Credit Type | Text | Credit type codes according to credit characteristics (such as being cash or non-cash) |
| Credit Open Date | Date | Date of credit issuance to the client |
| Credit Period | Date | Date of credit closing |
| Credit Conversion Factor | Number | Conversion factor for cash/non-cash credits |
| Credit Risk Class | Text | Credit risk class according to the regulation (8) |
| Currency Code | Text | Currency code of the credit issued |
| Credit Price Volatility | Number | Volatility adjustment |
| Credit Principal | Currency | Principal amount of the credit |
| Credit Interest | Currency | Accumulated interest amount of the credit |
| Provision/Loss | Currency | Provision/amortization/impairment amount if exits |
| Rating Grade | Text | Rating grade of the client |
| Credit Quality Level | Number | Credit quality level that rating grade matches |
| Credit Risk Weight | Number | Risk weight of the credit before CRM by collateral |
| Exposure Before CRM | Currency | Credit exposure value before using CRM technique |
| RWA After CRM | Currency | Risk-weighted credit exposure value after using CRM technique |
| Balance Sheet Class | Number | Balance sheet number of the credit |
| TB or BB | Text | If the credit is recorded under “trading book” or “banking book” |
| Foreign Exchange Indexed | Text | If the credit indexed to any foreign currency |
| CRA Rating1 | Text | Rating grade given by credit rating agency 1 |
| CRA Rating2 | Text | Rating grade given by credit rating agency 2 |
| CRA Rating3 | Text | Rating grade given by credit rating agency 3 |
| CRA Rating4 | Text | Rating grade given by credit rating agency 4 |
| OECD Rating | Text | OECD grade |

Credits table contains information regarding transactions or credits of clients. This table contains information belonging to obligors and transactions. It also includes information regarding calculation of risk-weighted exposure amount for each transaction record.

Collaterals table includes information regarding collaterals of clients. Information regarding both benefiter and warrantor of the collateral is provided as well as detailed information belonging to the collateral itself and its use on a specific credit of the client.

**Table 14** Collaterals table and its fields

| **COLLATERALS** | | |
|---|---|---|
| **Field Name** | **Data Type** | **Description** |
| Client ID | Number | Client ID given by the bank |
| Client Tax ID | Number | Tax ID or citizenship ID of the client |
| Trial Balance Code | Text | Trial balance record number of the credit |
| Warrantor Tax ID | Number | Tax ID or citizenship ID of the warrantor |
| Collateral ID | Text | Collateral ID number |
| Collateral Type | Text | Collateral type |
| Currency Code | Text | Currency code of the collateral |
| Warrantor Risk Class | Text | Risk class of the warrantor |
| Collateral Fair Value | Currency | Fair value of the collateral |
| Mortgage Value | Currency | Mortgage value of the collateral |
| Collateral Value Allocated | Currency | Collateral value considered for the relevant credit |
| Collateral Currency Volatility | Number | Currency volatility value for the collateral |
| Collateral Price Volatility | Number | Price volatility value for the collateral |
| Maturity Adjustment | Number | Maturity adjustment value for the collateral |
| Collateral Value After Adjustment | Currency | Collateral value calculated after the adjustments |
| Rating Grade | Text | Rating grade of the collateral |
| Collateral Risk Weight | Number | Risk weight of the collateral |
| Collateral Country Code | Text | Country code of the collateral |
| Collateral Period | Date | Last date collateral is valid |
| Warrantor Client ID | Text | Client ID of the warrantor if exists |
| Appraisal Firm Name/Code | Text | Name/code of the real estate appraisal firm |
| Last Appraisal Date | Date | Last appraisal date of the collateral |
| Mortgage No | Text | Mortgage number of the collateral |
| Mortgage Degree | Text | Degree of the mortgage |
| Appraisal Report Code | Text | Code number of the appraisal report |
| CRA Rating1 | Text | Rating grade given by credit rating agency 1 |
| CRA Rating2 | Text | Rating grade given by credit rating agency 2 |
| CRA Rating3 | Text | Rating grade given by credit rating agency 3 |
| CRA Rating4 | Text | Rating grade given by credit rating agency 4 |
| OECD Rating | Text | OECD grade |

### 4.1.2 Evaluation of Data Forms

In section 3.2.1.1, we categorized credit risk data under three main entities in accordance with the Basel framework. These are obligors, transactions and credit providers. Such categorization is formed in order to provide general schema of the credit risk components. Data template constructed by BRSA has a similar categorization. It consists of clients, credits, collaterals and repo and reverse repo transactions. However, fields and contents of these tables need to be discussed in terms of their effectiveness and efficiency. That is to say, data normalization is required for eliminating redundancies and ensuring dependency of dependent fields. Such normalization which leads to removal of transitive dependency contributes to reduction of data amount duplicated and achievement of data integrity.

Data tables presented by BRSA can be criticized in several aspects bearing the requirements of relational database in mind. One problem is the existence of redundant fields which can be removed as their presence is not necessary for credit risk management purposes or as they address similar information provided by other fields. Another problem is aggregation of various fields in one table which causes duplication of the same fields for each record. Decomposition of certain tables to sub tables is necessary to eliminate such duplication and provide integrity among records. Complexity of data structure can be minimized with decomposing and reorganizing data table schemas that also foster comprehensibility of tables in terms of data users in risk management.

Decomposition of credit risk data to viable data tables is prerequisite condition for ensuring DQ of credit risk. Avoiding continuous repetition of certain data fields is desired to achieve decrease in data amount to be stored and eliminate potential database errors such as incompatibilities among records due to duplication. Performing PK/FK analysis cited in Section 3.2.2.2 is crucial for normalization of data tables, i.e. systematic decomposition of them. The analysis involves detection of the best candidate fields for PKs and FKs.

Data table schema of clients proposed by BRSA does not require further decomposition since it has sufficient information for client characteristics and there is no repetition of any record upon involvement of a new transaction. However, data table schemas of credits and collaterals require further decomposition due to duplication of records when collaterals are attempted to be matched to collaterals for credit risk mitigation and calculation. In fact, a new relationship table is required to be formed for new instances of such matching process. To exemplify, a credit entity can be covered by a collateral entity or more than one collateral entity, or it cannot be covered by a collateral entity at all. Similarly, collateral may cover one or more credit entities, or it may not cover any credit entity. In brief, they have a many-to-many relationship. The problem arises due to the application of different risk weights to the covered and uncovered portions of a credit. Furthermore, credit risk class of the covered portion of a credit may even change in certain cases such as mortgage credits. Therefore, a credit or a collateral entity might be divided into more than one record. If not decomposed, that would cause duplication of all characteristics of a credit or collateral, which increases the size of data. In addition, such a scheme would increase complexity of risk calculation leading it to be prone to error. Example cases for matching collaterals to credits and resulting entry numbers for each case are provided in Figure 7. Thus, a new relationship table that can be formed by decomposing certain data fields existing in credits and collateral tables is required.

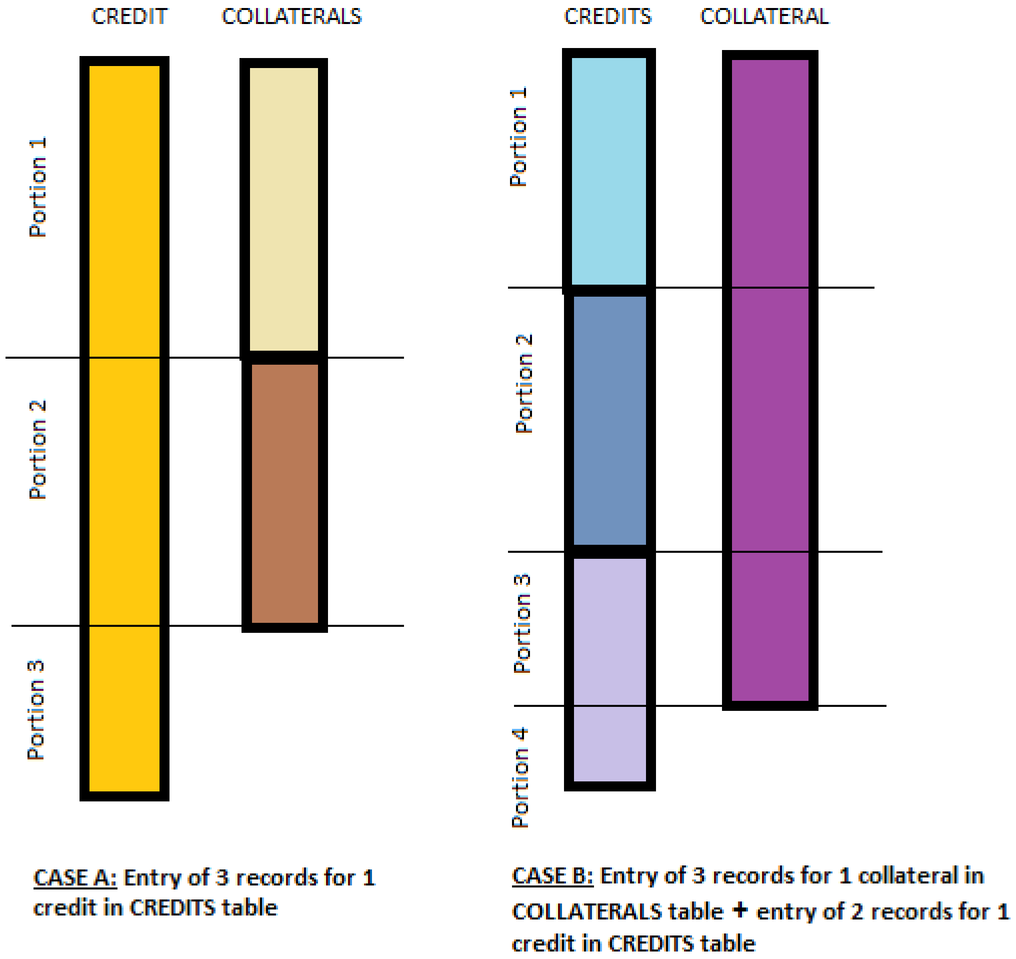

CREDIT
COLLATERALS
Portion 1
Portion 2
Portion 3
CASE A: Entry of 3 records for 1 credit in CREDITS table
CREDITS
COLLATERAL
Portion 1
Portion 2
Portion 3
Portion 4
CASE B: Entry of 3 records for 1 collateral in COLLATERALS table + entry of 2 records for 1 credit in CREDITS table

**Figure 7** Example cases for data duplication due to credit and collateral matching

Decomposition of data tables of credit and collaterals proposed by BRSA to form a new data table should be performed by considering following criteria:

- Credits table should contain a sufficient number of data fields to represent all relevant characteristics of a credit entity.
- Uniqueness of credits in the credits table should be ensured (PK detection).
- Collaterals table should contain a sufficient number of data fields to represent all relevant characteristics of a collateral entity.
- Uniqueness of collaterals in the collaterals table should be ensured (PK detection).
- Data fields belonging to either credits table or collaterals table that can be derived from the relationship of collaterals and credits should be transferred to the new data table schema.
- Key identifiers of the new data table should be determined. That is, identifiers and characteristics of clients, credits and collaterals should consistently be represented in the new data table (FK detection).

Considering these criteria, a new data table named “Credit Risk” is created by transferring certain fields from the existing data tables as well as adding new ones. The schemas of existing tables are also modified accordingly.

Credit Risk table contains information belonging to clients, credits and collaterals. Identifiers of these three entities are represented in the new table. Since there was no unique identifier for credits table, a new data field uniquely identifying a credit entity named “Credit ID” is created which is also represented in the new table. Due to creation of new table, certain data fields become redundant. Identification of redundant data can be performed via cross-domain analysis cited in Section 3.2.2.2. One application area of cross-domain analysis involves detection of identification of redundant data across columns in the same or different data tables. Redundancy of a field can be uncovered by analyzing its relation to another field existing in the same table or different data table. Elimination of redundant data is key to the process of normalization of data tables. Redundant fields that can be removed without concern of data loss in terms of credit risk management and causes for their redundancy are provided in Table 15.

**Table 15** Redundant fields that can be removed conveniently

| Field Name | Table Name | Cause for redundancy |
|---|---|---|
| Tax ID | Credits | Credits table contains information only for credits, it is not required in this table |
| Client ID | Credits | A new identifier field (Credit ID) is created for credits, client ID is not required anymore since it is represented in clients and credit risk table |
| Client ID | Collaterals | Collaterals table contains only information for collaterals, relationships are transferred to credit risk table via “Client ID” field. |
| Client Tax ID | Collaterals | Collaterals table contains information only for collaterals, it is not required in this table |
| Trial Balance Code | Collaterals | Collaterals table contains information only for collaterals, it is not required in this table |
| Warrantor Client ID | Collaterals | Warrantor tax ID is sufficient for identification of the warrantor, warrantor client is irrelevant |

Only fields required are transferred or copied to credit risk table to prevent duplicate records. Transferred fields correspond to the fields removed from the original table and added to the new table while copied fields correspond to the fields which are both presented in the original table and the new table. In other words, they form foreign keys of credit risk table which are used to establish relationship the tables of obligors, credits and collaterals. These are the primary keys of these tables as well as identifiers of them.

In addition to creation of “Credit ID” field as a primary key in credits table, a new field also created in credit risk table named “Final Risk Weight”. This new field is required to assign resulting risk weight to be applied to the credit portion of the exposure which is either covered or uncovered (see Figure 7). Final risk weight is determined by comparison between “credit risk weight” field from credits table and “collateral risk weight” in collaterals table. Figure 8 summarizes the process of decomposition of existing tables to form a relational data table. Fields removed, added, transferred and copied are provided in the figure. Statistics for such modification in the tables and the fields are also provided in Table 16. Although total number of data fields slightly change, the effect on data amount stored can significantly vary depending on the relationship among the entities of clients, credits and collaterals.

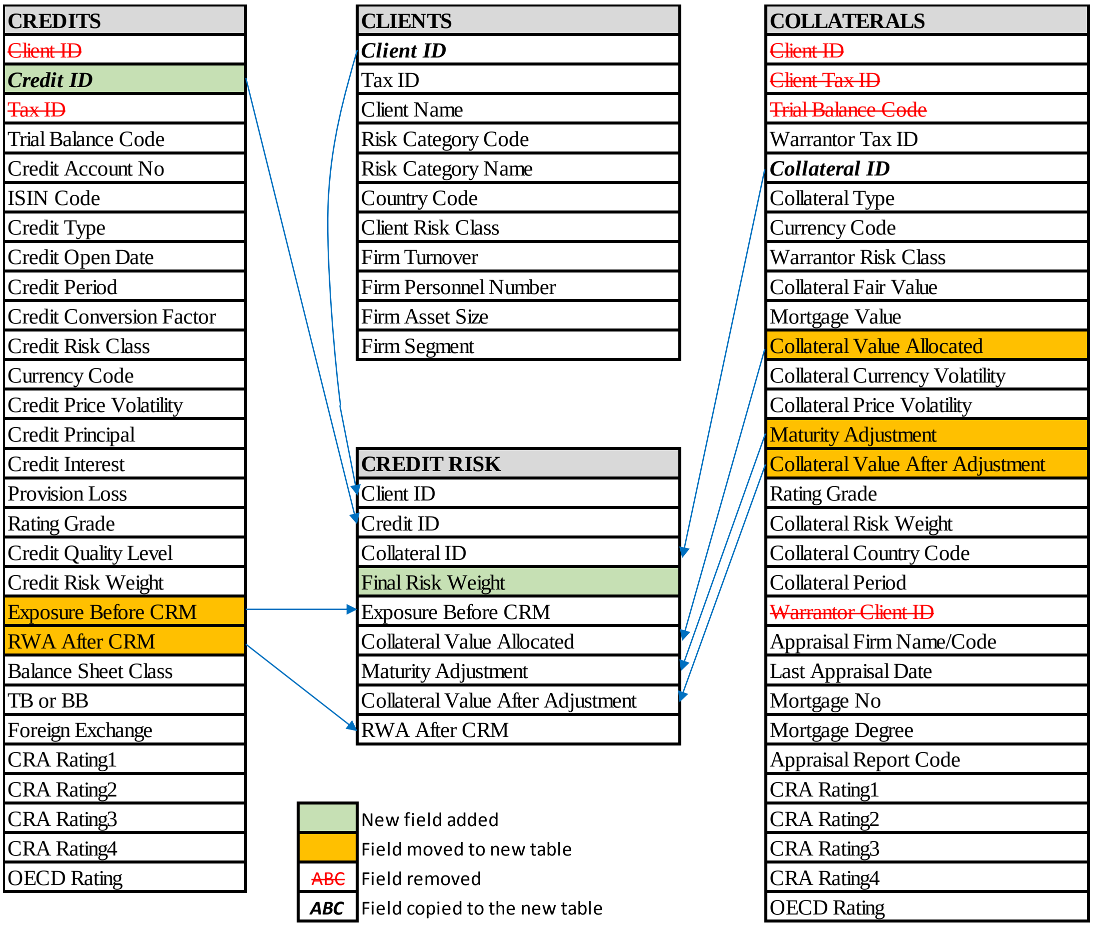


**Figure 8** Decomposition of existing data tables to form a new data table (Credit Risk)

**Table 16** Statistics for change in data field numbers of data tables

| Table Name | Existing field number | Added field number | Removed/transferred field number | New field number |
|---|---|---|---|---|
| Clients | 11 | - | - | 11 |
| Credits | 29 | 1 | 4 | 26 |
| Collaterals | 30 | - | 7 | 23 |
| Credit Risk | - | 9 | - | 9 |
| ***Total*** | ***70*** | ***10*** | ***11*** | ***69*** |

The effect of the new schema on data amount to be stored can be illustrated as follows: Let us say a bank has X number of clients, and Y number of credits and Z number of collaterals belonging to those clients. Considering existing schemas of data tables; 11 data fields for clients would have X records for clients table. Due to multiplication of records for certain credits and collaterals in the tables of credits and collaterals, lower record limits would be Y for credits table and Z for collaterals table. On the other hand, upper limit for both tables would be Y times Z.

*Client record number = X (11 fields)*

$Y \leq \textit{Credit record number} \leq Y \times Z$ *(29 fields)*

*$Z \leq$ Collateral record number $\leq Y \times Z$ (30 fields)*

However, after formation of the new schemas, the boundaries for record numbers for the respective tables in addition to the new data table will change. While record numbers of clients, credits and collaterals will be exactly X, Y and Z, respectively; the relationship table, i.e. credit risk table, will change from zero (no instance due to no allocation of collaterals to any credit) to Y times Z (not practical though).

*Client record number = X (11 fields)*

*Credit record number = Y (26 fields)*

*Collateral record number = Z (23 fields)*

*$0 \leq$ Credit risk record number $\leq Y \times Z$ (9 fields)*

An interesting conclusion can be inferred from these constraints. As the relationship among credits and collaterals gets complicated, i.e. higher number of instances where a credit is covered by multiple collaterals of the client or collateral covers multiple credits; record numbers get closer to the upper limit of the boundaries. In such cases, data amount that has to be stored in existing schema would exceed that in the new schema. The reason for this is trivial. (29 – 9) fields for credits and (30 – 9) fields for collaterals would not be duplicated in the new situation.

The amount of data to be stored under the existing and the new schemas has been compared on dummy values for number of clients (X), number of credits (Y) and number of collaterals (Z). Assumptions for the inputs of the comparison are as follows:

- A client has 3 credits on average ($Y = 3 \times X$).
- A client has 1,5 collaterals on average ($Z = 1{,}5 \times X$).
- The number of records in the Credits Table is Y times $k_{credit}$ factor for the existing schema. For example, if $k_{credit} = 2$ then each credit occupy two records on average.
- The number of records in the Credits Table is Y times $k_{collateral}$ factor for the existing schema. For example, if $k_{collateral} = 2$ then each credit will occupy two records on average.
- The number of records in the Credit Risk Table is $k_{relation}$ times maximum of Y and Z for the new schema. For example, if $k_{relation} = 2$ then the number of records in the Credit Risk Table will be $2 \times \max(Y, Z)$ on average.
- Increase in X, Y and Z is proportional to each other as data size increases.
- Total number of data values in all tables is considered as basis of comparison for data amount in the existing and new schemas.
- Total number of data values (number of data cells) of a table is calculated by multiplying the number of fields in a table by the number of records in it.

Based on the assumptions listed, various k-factor values are used to plot total number of data values for the existing and the new schemas. K-factor values of 1, 1,5 and 2,5 are used for $k_{credit}$, $k_{collateral}$ and $k_{relation}$. Results of the analysis are presented in Figure 9, Figure 10 and Figure 11.

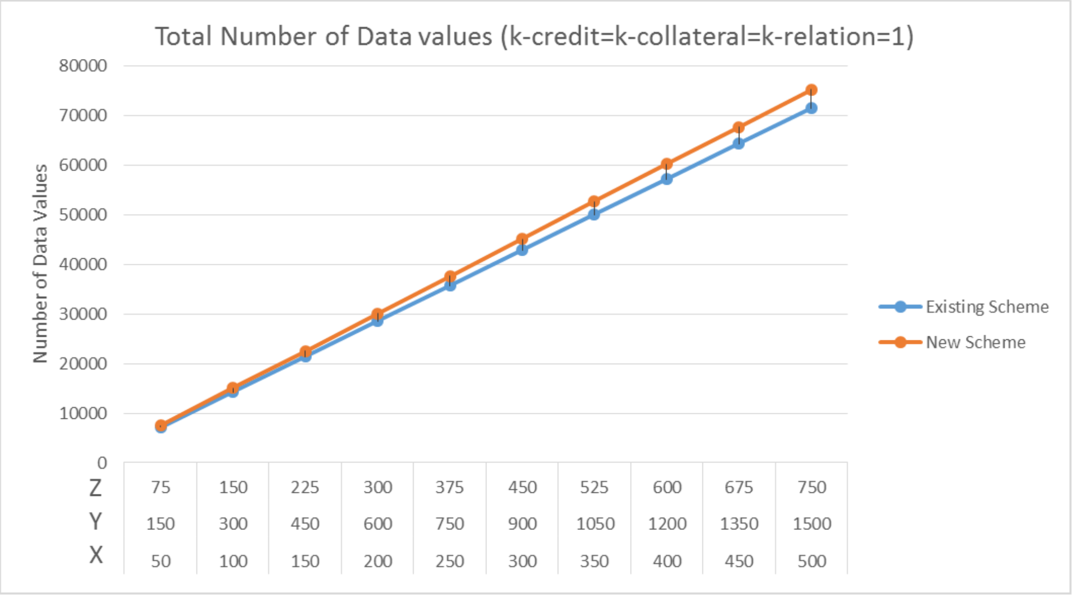


**Figure 9** Comparison of total number of data values between the existing and the new schemas (all k-factors=1)

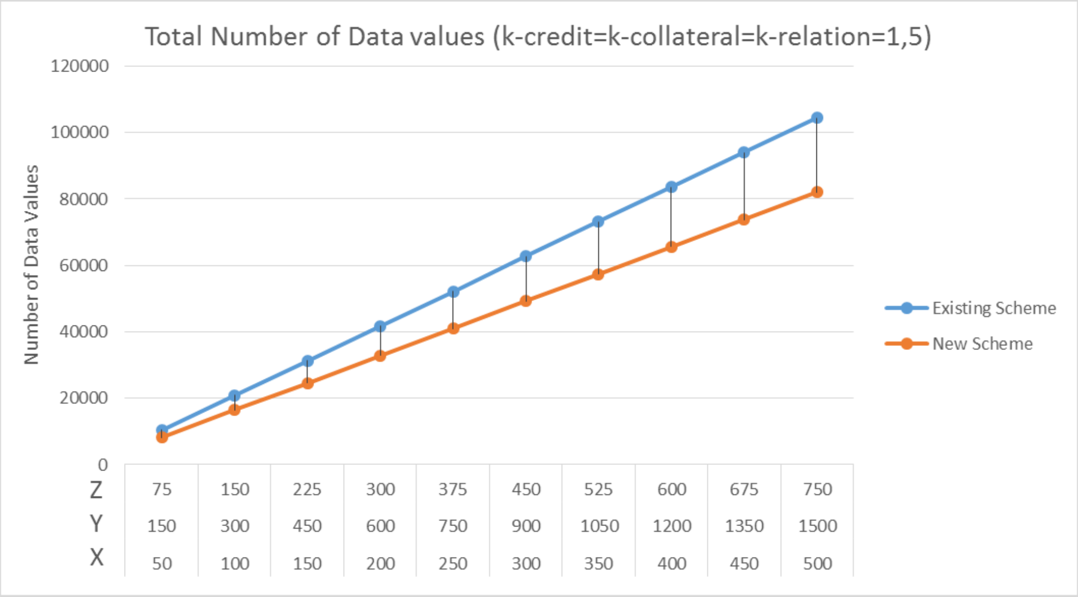


**Figure 10** Comparison of total number of data values between the existing and the new schemas (all k-factors=1,5)

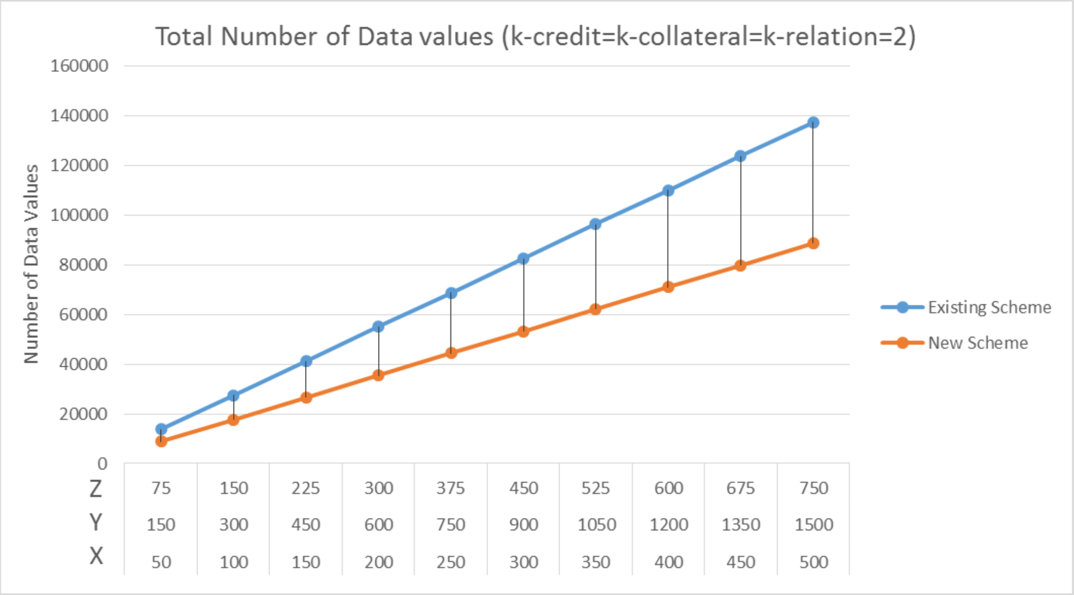


**Figure 11** Comparison of total number of data values between the existing and the new schemas (all k-factors=2)

When exact match of credits with collaterals are observed, i.e. one-to-one relation exits and no uncovered portion remains when a credit is covered, which is not a practical case, data amount that needs to be maintained for the two schemas are fairly close to each other; though new schema has slightly higher amount of data provided in Figure 9. As the interaction between credits and collaterals table gets sophisticated, more data storage area is required for the existing schema than that of the new schema as observed in Figure 10 and Figure 11.

## 4.2 Data Quality Assessment: A Bank Case

In this section, we are going to assess DQ of credit risk data of an actual bank operating in Turkey using TDQM phases tailored for credit risk in Chapter 3. The name of the bank will be kept confidential due to privacy reasons. We denote this bank as “ABC Bank”. Credit risk data dates to February of 2015. It consists of data belonging to clients, credits and collaterals of ABC Bank which is submitted in the form of the existing schema of data tables prepared by BRSA. Statistics for these tables are provided in Table 17.

**Table 17** Statistics for credit risk data tables of ABC Bank

| Data table name | Data field number | Average number of record per client/credit/collateral |
|---|---|---|
| Clients | 11 | 1 |
| Credits | 29 | 1,18 |
| Collaterals | 30 | 1,99 |

DQ dimensions for the fields of the existing tables will be explored in Section 4.2.1.

### 4.2.1 DQ dimensions for credit risk data of ABC Bank

We have defined DQ dimensions for data entities and its attributes of generic credit risk data in 3.2.1.3. DQ dimensions for DQA for data tables of ABC Bank should be determined accordingly. Data fields and relevant DQ dimensions for clients table are provided in Table 18.

**Table 18** DQ dimensions for clients table of ABC Bank

| **CLIENTS** | | |
|---|---|---|
| **Field Name** | **DQ Dimensions** | **Domain Set** |
| Client ID | Uniqueness, completeness, consistency (with Tax ID) | |
| Tax ID | Uniqueness, completeness, consistency (with Client ID) | |
| Client Name | Completeness, consistency (with client ID) | |
| Risk Category Code | Completeness, consistency (with Risk Category Name) | |
| Risk Category Name | Completeness, consistency (with Risk Category Code) | |
| Country Code | Completeness, accuracy | Country code is set according to ISO 3166-1 alpha-2 codes |
| Client Risk Class | Completeness, accuracy, consistency (with Firm Segment) | MRS1 to MRS13 |
| Firm Turnover | Consistency (with Firm Segment, Client Risk Class) | |
| Firm Staff Size | Consistency (with Firm Segment, Client Risk Class) | |
| Firm Asset Size | Consistency (with Firm Segment, Client Risk Class) | |
| Firm Segment | Accuracy, consistency (with Firm Turnover, Firm Staff Size, Firm Asset Size, Client Risk Class) | KOBI (SME) or KI (Corporate) |

Client ID and Tax ID of a client must be available for each customer. Client ID is assigned by the bank while Tax ID is obtained from the clients. National identity number (e.g. TCKN for Turkish citizens) is provided for real persons rather than tax ID number in Tax ID field. Client ID and Tax ID fields must be unique for each client. In addition, both must be consistent; that is, there must be one-to-one relationship between them. Client Name must also be consistent with Client ID. Similar rule applies to the fields Risk Category Code and Risk Category Name due to one-to-one relationship between them. Firm Segment can be either a SME, a corporate or null. If it is type of SME or corporate then Firm Turnover, Firm Staff Size and Firm Asset Size must be complete. Otherwise, all these fields must be null. Client Risk Class must also be consistent with Firm Segment. For example, if firm segment is type of SME then client risk class must be either MRS8 (corporate exposures to SME) or MRS9 (retail exposures to SME).

Data fields and relevant DQ dimensions for credits table are provided in Table 19.

**Table 19** DQ dimensions for credits table of ABC Bank

| CREDITS | | |
|---|---|---|
| **Field Name** | **DQ Dimensions** | **Domain Set** |
| Client ID | Completeness, consistency (with Tax ID) | |
| Tax ID | Completeness, consistency (with Client ID) | |
| Trial Balance Code | Completeness, accuracy | In accordance with Turkish Accounting Standards (TAS – TMS in Turkish) |
| Credit Account No | Completeness | |
| ISIN Code | Accuracy | Structure is according to ISO 6166, 12-character alpha numerical code |
| Credit Type | Completeness, accuracy | NK or NKKF (for cash credits), GNAxx, GNBxx, GNCxx or GNDxx (for non-cash credits), KTRxxx (for counterparty risk), DA (for other credits) |
| Credit Open Date | Completeness, timeliness | |
| Credit Period | Completeness, timeliness | |
| Credit Conversion Factor | Completeness, accuracy, consistency (with Credit Type) | 0%, 20%, 50% or 100% |
| Credit Risk Class | Completeness, accuracy | ARS01 to ARS19 |
| Currency Code | Completeness, accuracy | Currency code is set according to ISO 4217 standards |
| Credit Price Volatility | - | |
| Credit Principal | Completeness | |
| Credit Interest | - | |
| Provision Loss | - | |
| Rating Grade | Accuracy | Depends on the rating scale of CRA used |
| Credit Quality Level | Accuracy | 1 to 6 |
| Credit Risk Weight | Completeness, accuracy | 0%, 20%, 50%, 75%, 100%, 150%, 200%, 250% |
| Exposure Before CRM | Completeness | |
| RWA After CRM | Completeness | |
| Balance Sheet Class | Completeness, accuracy | 1 to 20, or 27, 48, 50 or 51 |
| TB or BB | Completeness, accuracy | TB or BB |
| Foreign Exchange Indexed | Accuracy | Y (Yes) or null |
| CRA Rating1 | Accuracy | Depends on the rating scale of CRA |
| CRA Rating2 | Accuracy | Depends on the rating scale of CRA |
| CRA Rating3 | Accuracy | Depends on the rating scale of CRA |
| CRA Rating4 | Accuracy | Depends on the rating scale of CRA |
| OECD Rating | Accuracy | The rating scale of OECD |

Data fields and relevant DQ dimensions for collaterals table are provided in Table 20.

**Table 20** DQ dimensions for collaterals table of ABC Bank

| COLLATERALS | | |
|---|---|---|
| **Field Name** | **DQ Dimensions** | **Domain Set** |
| Client ID | Completeness, consistency (with Tax ID) | |
| Client Tax ID | Completeness, consistency (with Client ID) | |
| Trial Balance Code | Completeness | |
| Warrantor Tax ID | Completeness, consistency (with Warrantor Client ID) | |
| Collateral ID | Completeness | |
| Collateral Type | Completeness, accuracy | T1-T12 |
| Currency Code | Completeness, accuracy | Currency code is set according to ISO 4217 standards |
| Warrantor Risk Class | Completeness, accuracy | TRS01-TRS16 |
| Collateral Fair Value | Completeness, consistency (with Collateral Type) | |
| Mortgage Value | Consistency (with Collateral Type) | |
| Collateral Value Allocated | Completeness | |
| Collateral Currency Volatility | Consistency (with Collateral Value After Adjustment) | |
| Collateral Price Volatility | Consistency (with Collateral Value After Adjustment) | |
| Maturity Adjustment | Consistency (with Collateral Value After Adjustment) | |
| Collateral Value After Adjustment | Consistency (with Collateral Price Volatility) | |
| Rating Grade | Accuracy | |
| Collateral Risk Weight | Accuracy | 0%, 20%, 50%, 75%, 100%, 150%, 200%, 250% |
| Collateral Country Code | Completeness, Accuracy | Country code is set according to ISO 3166-1 alpha-2 codes |
| Collateral Period | Completeness | |
| Warrantor Client ID | - | |
| Appraisal Firm Name/Code | Consistency (with Collateral Type) | |
| Last Appraisal Date | Consistency (with Collateral Type) | |
| Mortgage No | Consistency (with Collateral Type) | |
| Mortgage Degree | Accuracy, consistency (with Collateral Type) | 1 to 3 |
| Appraisal Report Code | Consistency (with Collateral Type) | |
| CRA Rating1 | Accuracy | Depends on the rating scale of CRA |
| CRA Rating2 | Accuracy | Depends on the rating scale of CRA |
| CRA Rating3 | Accuracy | Depends on the rating scale of CRA |
| CRA Rating4 | Accuracy | Depends on the rating scale of CRA |
| OECD Rating | Accuracy | The rating scale of OECD |

### 4.2.2 DQ metrics for ABC Bank

DQ metrics for generic credit risk data were defined in Section 3.2.2.1 in accordance with DQ dimensions identified in Section 3.2.1.3. Now we are going to define DQ metrics for DQA of credit risk data of ABC Bank accordingly. The metrics defined below are expressed in more general terms since they have similar structure for a given DQ dimension regardless of the field in concern. However, there can be differences in details of the metric for accuracy and consistency dimension since DQ metrics related to these dimensions depend on specific business rules, i.e. they are context dependent. This section contains identification of DQ metrics for credit risk data of ABC Bank, Structured Query Language (SQL) queries for measurement of the metrics identified and results of these queries.

#### 4.2.2.1 Identification of DQ metrics

DQ metrics for DQ dimensions necessary for DQA of credit risk data of ABC Bank are identified in this section.

**Uniqueness**

The following metric applies to all fields that requires fulfillment of uniqueness dimension indicated in Table 18.

- Total number of records in clients table that have duplicate records for certain FIELD that must be unique to total number of all records in the table

**Accuracy**

The following metric applies to all fields that requires fulfillment of accuracy dimension indicated in Table 18, Table 19 and Table 20.

- Total number of records in clients/credits/collaterals table whose certain FIELD violates domain constraints of that field to total number of all records in the table (clients/credits/collaterals)

**Completeness**

The following metric applies to all fields that requires fulfillment of completeness dimension indicated in Table 18, Table 19 and Table 20.

- Total number of records in clients/credits/collaterals table whose certain FIELD that must be non-null is null to total number of all records in the table (clients/credits/collaterals)

**Consistency**

The following metric applies to all fields that requires fulfillment of completeness dimension indicated in Table 18, Table 19 and Table 20.

- Total number of records in clients/credits/collaterals table whose certain FIELD value contradicts with the value(s) of other dependent fields(s) to total number of all records in the table (clients/credits/collaterals)

**Timeliness**

The following metric applies to all fields that requires fulfillment of timeliness dimension indicated in Table 19 and Table 20.

- Total number of records in credits/collaterals table whose certain FIELD was updated before date DD.MM.YYYY to total number of all records in the table (credits/collaterals)

#### 4.2.2.2 SQL queries for measurement of DQ metrics

SQL queries are extensively used in data profiling which is referred as the process of examining the data available in an existing data source and collecting statistics and information about that data[3]. SQL queries are required for data profiling since it involves dealing with complex algorithms (Naumann, 2013). Data profiling addresses quantitative aspect of DQA. Therefore, SQL queries can be useful in applying the DQA methods described in Section 3.2.2.2. Credit risk data of ABC Bank available in hand can allow to carry out PK/FK analysis, column analysis, cross-domain analysis, domain analysis and semantic profiling. DQ metrics defined for credit risk data of ABC bank can be expressed via SQL queries. Results of SQL queries can be used to evaluate performance of DQ metrics. Structures of SQL queries for the DQ dimensions identified are provided as follows:

SQL query for identifying violations of uniqueness:

Violation of uniqueness for a unique field can be detected by finding duplicate records in that field. Column analysis can be performed to detect such duplicates. Use of the following SQL query is one way to perform column analysis for detection of duplicate records. The query will bring out the records having duplicates along with the number of duplication times.

"SELECT Field_Name, COUNT(Field_Name) FROM Table_Name GROUP BY Field_Name HAVING COUNT(Field_Name) > 1"

The result of the query is not enough. Summing duplication times less one of all the records displayed and comparing it to the total number of all records in the table will produce a DQ metric for assessment uniqueness dimension of the field. Specific SQL queries used for assessing uniqueness dimension are provided in APPENDIX B.

SQL query for identifying violations of completeness:

Violation of completeness requirement of a field can be detected by finding null values in that field. Column analysis can be performed to detect such null values. Use of the following SQL query is one way to perform column analysis for detection null values. The query will bring out the number of null values in that field.

"SELECT COUNT(*) FROM Table_Name WHERE Field_Name Is Null"

Comparing the result of the query to the total number of records in the table will produce a DQ metric for assessment of completeness dimension of the field. Specific

[3] https://en.wikipedia.org/wiki/Data_profiling

SQL queries used for assessing completeness dimension are provided in APPENDIX B.

SQL queries for identifying violations of accuracy:

Detection of violation of accuracy for a field can be tricky due to its dependence on the domain constraints of the field. Domain constraints are usually mandated by business rules. Domain analysis can be performed to detect violation of the domain constraints. Use of the following SQL query is one way to perform domain analysis to the fields of tables of credit risk data. The query is a more general form for detection of violation of domain constraints. Conditions are imposed on the relevant field to check whether the record value for the field satisfy the range of the domain specified.

"SELECT COUNT(*) FROM Table_Name WHERE Field_Name1 [Operator1] *Value1* AND/OR Field_Name1 [Operator2] *Value2* AND/OR … AND/OR Field_Name1 [OperatorN] *ValueN*"

*Value1* to *ValueN* denote values for domain constraints while *Operator1* to *OperatorN* denote operators that prevent to meet domain constraints. Comparing the result of such a query to the total number of records in concerning table will produce a DQ metric for assessment of accuracy dimension of the field. Specific SQL queries used for assessing accuracy dimension are provided in APPENDIX B.

SQL queries for identifying violations of consistency:

Detection of violation of consistency for a field can be tricky due to its dependence on the business rules imposed and relationships among the fields. Cross-domain analysis and semantic profiling can be performed to detect inconsistencies among several fields. The following SQL query is a more general form for detection of violation of business rules among different fields. The query involves monitoring more than one field.

"SELECT COUNT(*) FROM Table_Name WHERE Field_Name1 [Operator1] *Value1* AND/OR Field_Name2 [Operator2] *Value2* AND/OR … AND/OR Field_NameN [OperatorN] *ValueN*"

*Value1* to *ValueN* denote values for domain constraints while *Operator1* to *OperatorN* denote operators that prevent to meet business rules. The query can be used as an example of performing cross-domain analysis and semantic profiling. Comparing the result of such a query to the total number of records in concerning table will produce a DQ metric for assessment of consistency dimension of the field. Specific SQL queries used for assessing consistency dimension are provided in APPENDIX B.

SQL queries for identifying violations of timeliness:

Since there is no specific information on when credit risk data values of ABC Bank are updated, no SQL query is built for the timeliness dimension.

#### 4.2.2.3 Results of calculation of DQ metrics for credit risk data of ABC Bank

Calculation of DQ metrics for credit risk data of ABC Bank identified in Section 4.2.2.1 via SQL queries created in Section 4.2.2.2 will be performed in this section.

Specific SQL queries created for credit risk data tables of ABC Bank are provided in APPENDIX B.

DQ metrics for each dimension are calculated and provided in Table 21, Table 22, Table 23 and Table 24. The metrics refer to violation rates which are calculated by proportioning number of observed violations in a table to total number of records in that table.

**Table 21** Results of SQL queries for uniqueness dimension

| DQ Metric Code | Relevant Field(s) | Reference Table | Violation Rate | Reference SQL Query (**APPENDIX B**) |
|---|---|---|---|---|
| **UNQ1** | Client ID | Clients | 0% | Query1 |
| **UNQ2** | Tax ID | Clients | 0,01% | Query2 |

**Table 22** Results of SQL queries for completeness dimension

| DQ Metric Code | Relevant Field(s) | Reference Table | Violation Rate | Reference SQL Query (**APPENDIX B**) |
|---|---|---|---|---|
| **CMP1** | Client ID | Clients | 0% | Query3 |
| **CMP2** | Tax ID | Clients | 54,92% | Query4 |
| **CMP3** | Client Name | Clients | 0% | Query5 |
| **CMP4** | Risk Cat. Code | Clients | 89,75% | Query6 |
| **CMP5** | Risk Cat. Name | Clients | 89,75% | Query7 |
| **CMP6** | Country Code | Clients | 0% | Query8 |
| **CMP7** | Cl. Risk Class | Clients | 0% | Query9 |
| **CMP8** | Client ID | Credits | 0% | Query10 |
| **CMP9** | Tax ID | Credits | 42,21% | Query11 |
| **CMP10** | Credit Acc. No | Credits | 0% | Query12 |
| **CMP11** | Trial Bal. Code | Credits | 0% | Query13 |
| **CMP12** | Credit Type | Credits | 0% | Query14 |
| **CMP13** | Cr. Open Date | Credits | 0% | Query15 |
| **CMP14** | Credit Period | Credits | 0% | Query16 |
| **CMP15** | Cr. Conv. Fac. | Credits | 0% | Query17 |
| **CMP16** | Cr. Risk Class | Credits | 0% | Query18 |
| **CMP17** | Currency Code | Credits | 0% | Query19 |
| **CMP18** | Credit Principal | Credits | 0% | Query20 |
| **CMP19** | Cr. Risk Weight | Credits | 0% | Query21 |
| **CMP20** | Exp. Before CRM | Credits | 0% | Query22 |
| **CMP21** | RWA After CRM | Credits | 0% | Query23 |
| **CMP22** | Bal. Sheet Class | Credits | 0% | Query24 |
| **CMP23** | TB or BB | Credits | 0% | Query25 |
| **CMP24** | Client ID | Collaterals | 0% | Query26 |
| **CMP25** | Client Tax ID | Collaterals | 34,18% | Query27 |
| **CMP26** | Trial Bal. Code | Collaterals | 0% | Query28 |
| **CMP27** | Warrantor Tax ID | Collaterals | 33,45% | Query29 |
| **CMP28** | Collateral ID | Collaterals | 0% | Query30 |
| **CMP29** | Collateral Type | Collaterals | 0% | Query31 |
| **CMP30** | Currency Code | Collaterals | 0% | Query32 |
| **CMP31** | War. Risk Class | Collaterals | 0% | Query33 |
| **CMP32** | Coll. Fair Value | Collaterals | 0% | Query34 |
| **CMP33** | Coll. Value Alloc. | Collaterals | 0% | Query35 |
| **CMP34** | Coll. Coun. Code | Collaterals | 0% | Query36 |
| **CMP35** | Coll. Period | Collaterals | 0% | Query37 |

Number of violation of *uniqueness* is quite low. Tax ID of several clients has been duplicated in clients table cause of which should be investigated. Uniqueness dimension is not relevant to credits and collaterals tables of ABC Bank.

Certain fields from tables of clients, credits and collaterals contain significant rates of violations of *completeness*. More than half of records in clients table do not have tax IDs. Similar issues related to availability of tax IDs belonging to either clients or warrantors also exist in credits and collaterals table. Availability of risk category names and codes of the clients is quite low, as much as 10%.

**Table 23** Results of SQL queries for accuracy dimension

| DQ Metric Code | Relevant Field(s) | Reference Table | Violation Rate | Reference SQL Query (**APPENDIX B**) |
|---|---|---|---|---|
| **ACC1** | Client Risk Class | Clients | 0% | Query38 |
| **ACC2** | Firm Segment | Clients | 0% | Query39 |
| **ACC3** | Trial Bal. Code | Credits | 0% | Query40 |
| **ACC4** | Credit Type | Credits | 0% | Query41 |
| **ACC5** | Cr. Conv. Factor | Credits | 0% | Query42 |
| **ACC6** | Credit Risk Class | Credits | 0% | Query43 |
| **ACC7** | Cr. Quality Level | Credits | 0% | Query44 |
| **ACC8** | Cr. Risk Weight | Credits | 0% | Query45 |
| **ACC9** | Bal. Sheet Class | Credits | 0% | Query46 |
| **ACC10** | TB or BB | Credits | 0% | Query47 |
| **ACC11** | For. Exc. Indexed | Credits | 0% | Query48 |
| **ACC12** | Collateral Type | Collaterals | 0% | Query49 |
| **ACC13** | War. Risk Class | Collaterals | 0% | Query50 |
| **ACC14** | Coll. Risk Weight | Collaterals | 0% | Query51 |
| **ACC15** | Mortgage Degree | Collaterals | 0% | Query52 |

There is no violation observed in *accuracy* of the fields as their domain constraints are not violated.

*Inconsistencies* due to violation of business rules are observed in three areas in general. These are the violation of the rules imposed on firm segment (SME or corporate), risk category of and real estate collaterals of clients. Turnover, active size and staff size information of certain firms who are type of SME or corporate are not specified in clients table. Most of the real estate collaterals does not contain information about mortgage degree, mortgage number, mortgage value, and appraisal of the real estate (appraisal firm, appraisal report, last appraisal date).

There are total of 67 metrics have been identified for DQA of credit risk data of ABC Bank. Of these, 2 metrics belong to uniqueness dimension; 35 metrics belong to completeness dimension; 15 metrics belong to accuracy dimension and 15 metrics belong to consistency dimension.

**Table 24** Results of SQL queries for consistency dimension

| DQ Metric Code | Relevant Field(s) | Reference Table | Violation Rate | Reference SQL Query (**APPENDIX B**) |
|---|---|---|---|---|
| **CNS1** | Client ID, Tax ID | Clients | 0% | Query53 |
| **CNS2** | Tax ID, Client ID | Clients | 0,01% | Query54 |
| **CNS3** | Risk Cat. Code, Risk Cat. Name | Clients | 3,61% | Query55 |
| **CNS4** | Risk Cat. Name, Risk Cat. Code | Clients | 3,61% | Query56 |
| **CNS5** | Client Risk Class, Firm Segment | Clients | 0% | Query57 |
| **CNS6** | Firm Segment, Firm Turnover | Clients | 43,84% | Query58 |
| **CNS7** | Firm Segment, Staff Size | Clients | 6,28% | Query59 |
| **CNS8** | Firm Segment, Firm Asset Size | Clients | 38,31% | Query60 |
| **CNS9** | Credit Type, Credit Conv. Factor | Credits | 0% | Query61 |
| **CNS10** | Collateral Type, Mortgage Value | Collaterals | 87,68% | Query62 |
| **CNS11** | Collateral Type Mortgage Degree | Collaterals | 87,68% | Query63 |
| **CNS12** | Collateral Type, Mortgage No | Collaterals | 87,68% | Query64 |
| **CNS13** | Collateral Type, Appr. Firm Name | Collaterals | 87,68% | Query65 |
| **CNS14** | Collateral Type, Appr. Report Code | Collaterals | 87,68% | Query66 |
| **CNS15** | Collateral Type, Last Appraisal Date | Collaterals | 87,68% | Query67 |

### 4.2.2.4 KQPIs and CQPIs for DQA

The metrics identified in 4.2.2.1 can be transformed to KQPIs and CQPIs defined in 3.2.2.3 in order to evaluate quality performance of credit risk data of ABC Bank. Violations rates obtained in 4.2.2.3 can be used to calculate KQPIs and CQPIs. Deduction of violation rates from the total outcomes, i.e. 100%, will yield non-violation rates which can be transformed to standardized values that fall into certain standard scale. Then, each standardized value can denote a KQPI that represents performance of a field for a given DQ dimension. Weights for each KQPI can be determined according to the significance of the field for credit risk measurement and calculation. CQPI for each dimension can be constructed by summing up weighted KQPIs where sum of weights add up to one. In the case of credit risk data of ABC Bank, KQPI scale is used as the range between 0 and 10. KQPI having value of 10 means perfect quality performance in that field while value of 0 corresponds to the worst quality performance.

Weights of KQPI to form CQPI are determined based on four cases. In the first case (Case 1), all fields are treated equally. In other cases (Case 2, Case3 and Case 4), weights are determined according to significance of the fields for credit risk calculation.

For this purpose, data fields of the relevant tables are grouped under three clusters based on their effect on credit risk calculation as described in Section 3.2.2.3. Cluster A contains the fields which are directly represented as parameters in credit risk function. Cluster B contains the fields that affect the parameters in credit risk function. Cluster C contains the fields that do not have significant effect on credit risk calculation. The fields are clustered in Table 25.

Weights of each cluster, which are used to calculate CQPIs by weighted sums of KQPIs are determined based on their significance for credit risk calculation. Weights of the fields in Cluster C are taken zero for all three cases (Case 2, Case 3 and Case

4). Weights of Cluster A is taken greater than or equal to those of Cluster B. Weight of Cluster A and Cluster B are equal in Case 2 while Weight of Cluster A is two times higher in Case 3 and three times higher in Case 4 that that of Cluster B.

**Table 25** Clustering data fields of credit risk tables according to their significance for credit risk calculation

| Cluster Description | Data fields in the cluster | Weight for the cluster |
|---|---|---|
| ***Cluster A:*** *Fields directly represented as parameters in credit risk function* | Credit Period, Credit Conversion Factor, Credit Price Volatility, Credit Principal, Credit Interest, Provision/Loss, Credit Risk Weight, Exposure Before CRM, RWA After CRM, Collateral Fair Value, Collateral Value Allocated, Collateral Price Volatility, Maturity Adjustment, Collateral Value After Adjustment, Collateral Risk Weight, Collateral Period, Mortgage Value, Mortgage Degree | $W_a$ |
| ***Cluster B:*** *Fields affecting parameters in credit risk function* | Risk Category Code, Risk Category Name, (Client) Country Code, (Collateral) Country Code, Client Risk Class, Firm Turnover, Firm Staff Size, Firm Asset Size, Firm Segment, Trial Balance Code, Credit Type, Credit Open Date, Credit Risk Class, (Credit) Currency Code, (Collateral) Currency Code, (Obligor) Rating Grade, Credit Quality Level, Balance Sheet Class, TB or BB, Foreign Exchange Indexed, Collateral Type, Warrantor Risk Class, (Collateral) Rating Grade, CRA Rating1, CRA Rating2, CRA Rating3, CRA Rating4, OECD Rating | $W_b$ |
| ***Cluster C:*** *Fields not having significant effect on credit risk calculation* | Client ID, (Client) Tax ID, Client Name, Credit Account No, ISIN Code, Warrantor Tax ID, Collateral ID, Warrantor Client ID, Appraisal Firm Name/Code, Last Appraisal Date, Mortgage No, Appraisal Report Code | $W_c = 0$ |
| $\mathbf{W_a = k \times W_b}$ **; Cases: k = 1, 2, 3** | | |

Weights of each field are determined accordingly for uniqueness, completeness, accuracy and completeness dimensions and presented in Table 26, Table 27, Table 28 and Table 29, respectively. Calculation of KQPIs and CQPIs are performed in accordance with the formulas proposed in 3.2.2.3 for the DQ dimensions and results of CQPIs are presented in Table 30.

**Table 26** KQPIs and CQPIs for uniqueness dimension

| DQ Metric Code | Violation Rate | KQPI | Relevant Field(s) | Cluster | Weight (C:1) | Weight (C:2) (k=1) | Weight (C:3) (k=2) | Weight (C:4) (k=3) |
|---|---|---|---|---|---|---|---|---|
| **UNQ1** | 0% | 10 | Client ID | C | 0,5 | 0 | 0 | 0 |
| **UNQ2** | 0,01% | 9,999 | Tax ID | C | 0,5 | 0 | 0 | 0 |

**Table 27** KQPIs and CQPIs for completeness dimension

| DQ Metric Code | Violation Rate | KQPI | Relevant Field(s) | Cluster | Weight (C:1) | Weight (C:2) (k=1) | Weight (C:3) (k=2) | Weight (C:4) (k=3) |
|---|---|---|---|---|---|---|---|---|
| **CMP1** | 0% | 10 | Client ID | C | 0,029 | 0,000 | 0,000 | 0,000 |
| **CMP2** | 54,92% | 4,51 | Tax ID | C | 0,029 | 0,000 | 0,000 | 0,000 |
| **CMP3** | 0% | 10 | Client Name | C | 0,029 | 0,000 | 0,000 | 0,000 |
| **CMP4** | 89,75% | 1,03 | Risk Cat. Code | B | 0,029 | 0,040 | 0,029 | 0,023 |
| **CMP5** | 89,75% | 1,03 | Risk Cat. Name | B | 0,029 | 0,040 | 0,029 | 0,023 |
| **CMP6** | 0% | 10 | Country Code | B | 0,029 | 0,040 | 0,029 | 0,023 |
| **CMP7** | 0% | 10 | Client Risk Class | B | 0,029 | 0,040 | 0,029 | 0,023 |
| **CMP8** | 0% | 10 | Client ID | C | 0,029 | 0,000 | 0,000 | 0,000 |
| **CMP9** | 42,21% | 5,78 | Tax ID | C | 0,029 | 0,000 | 0,000 | 0,000 |
| **CMP10** | 0% | 10 | Credit Acc. No | C | 0,029 | 0,000 | 0,000 | 0,000 |
| **CMP11** | 0% | 10 | Trial Bal. Code | B | 0,029 | 0,040 | 0,029 | 0,023 |
| **CMP12** | 0% | 10 | Credit Type | B | 0,029 | 0,040 | 0,029 | 0,023 |
| **CMP13** | 0% | 10 | Credit Open Date | B | 0,029 | 0,040 | 0,029 | 0,023 |
| **CMP14** | 0% | 10 | Credit Period | A | 0,029 | 0,040 | 0,059 | 0,070 |
| **CMP15** | 0% | 10 | Credit Conv. Fac. | A | 0,029 | 0,040 | 0,059 | 0,070 |
| **CMP16** | 0% | 10 | Credit Risk Class | B | 0,029 | 0,040 | 0,029 | 0,023 |
| **CMP17** | 0% | 10 | Currency Code | B | 0,029 | 0,040 | 0,029 | 0,023 |
| **CMP18** | 0% | 10 | Credit Principal | A | 0,029 | 0,040 | 0,059 | 0,070 |
| **CMP19** | 0% | 10 | Cr. Risk Weight | A | 0,029 | 0,040 | 0,059 | 0,070 |
| **CMP20** | 0% | 10 | Exp. Before CRM | A | 0,029 | 0,040 | 0,059 | 0,070 |
| **CMP21** | 0% | 10 | RWA After CRM | A | 0,029 | 0,040 | 0,059 | 0,070 |
| **CMP22** | 0% | 10 | Bal. Sheet Class | B | 0,029 | 0,040 | 0,029 | 0,023 |
| **CMP23** | 0% | 10 | TB or BB | B | 0,029 | 0,040 | 0,029 | 0,023 |
| **CMP24** | 0% | 10 | Client ID | C | 0,029 | 0,000 | 0,000 | 0,000 |
| **CMP25** | 34,18% | 6,58 | Client Tax ID | C | 0,029 | 0,000 | 0,000 | 0,000 |
| **CMP26** | 0% | 10 | Trial Bal. Code | B | 0,029 | 0,040 | 0,029 | 0,023 |
| **CMP27** | 33,45% | 6,66 | Warrantor Tax ID | C | 0,029 | 0,000 | 0,000 | 0,000 |
| **CMP28** | 0% | 10 | Collateral ID | C | 0,029 | 0,000 | 0,000 | 0,000 |
| **CMP29** | 0% | 10 | Collateral Type | B | 0,029 | 0,040 | 0,029 | 0,023 |
| **CMP30** | 0% | 10 | Currency Code | B | 0,029 | 0,040 | 0,029 | 0,023 |
| **CMP31** | 0% | 10 | War. Risk Class | B | 0,029 | 0,040 | 0,029 | 0,023 |
| **CMP32** | 0% | 10 | Coll. Fair Value | A | 0,029 | 0,040 | 0,059 | 0,070 |
| **CMP33** | 0% | 10 | Coll. Value Alloc. | A | 0,029 | 0,040 | 0,059 | 0,070 |
| **CMP34** | 0% | 10 | Coll. Count. Code | B | 0,029 | 0,040 | 0,029 | 0,023 |
| **CMP35** | 0% | 10 | Collateral Period | A | 0,029 | 0,040 | 0,059 | 0,070 |

**Table 28** KQPIs and CQPIs for accuracy dimension

| DQ Metric Code | Violation Rate | KQPI | Relevant Field(s) | Cluster | Weight (C:1) | Weight (C:2) (k=1) | Weight (C:3) (k=2) | Weight (C:4) (k=3) |
|---|---|---|---|---|---|---|---|---|
| **ACC1** | 0% | 10 | Client Risk Class | B | 0,067 | 0,067 | 0,053 | 0,043 |
| **ACC2** | 0% | 10 | Firm Segment | B | 0,067 | 0,067 | 0,053 | 0,043 |
| **ACC3** | 0% | 10 | Trial Bal. Code | B | 0,067 | 0,067 | 0,053 | 0,043 |
| **ACC4** | 0% | 10 | Credit Type | B | 0,067 | 0,067 | 0,053 | 0,043 |
| **ACC5** | 0% | 10 | Credit Conv. Fac. | A | 0,067 | 0,067 | 0,105 | 0,130 |
| **ACC6** | 0% | 10 | Credit Risk Class | B | 0,067 | 0,067 | 0,053 | 0,043 |
| **ACC7** | 0% | 10 | Cr. Quality Level | B | 0,067 | 0,067 | 0,053 | 0,043 |
| **ACC8** | 0% | 10 | Cr. Risk Weight | A | 0,067 | 0,067 | 0,105 | 0,130 |
| **ACC9** | 0% | 10 | Bal. Sheet Class | B | 0,067 | 0,067 | 0,053 | 0,043 |
| **ACC10** | 0% | 10 | TB or BB | B | 0,067 | 0,067 | 0,053 | 0,043 |
| **ACC11** | 0% | 10 | For. Exc. Indexed | B | 0,067 | 0,067 | 0,053 | 0,043 |
| **ACC12** | 0% | 10 | Collateral Type | B | 0,067 | 0,067 | 0,053 | 0,043 |
| **ACC13** | 0% | 10 | War. Risk Class | B | 0,067 | 0,067 | 0,053 | 0,043 |
| **ACC14** | 0% | 10 | Coll. Risk Weight | A | 0,067 | 0,067 | 0,105 | 0,130 |
| **ACC15** | 0% | 10 | Mortgage Degree | A | 0,067 | 0,067 | 0,105 | 0,130 |

**Table 29** KQPIs and CQPIs for consistency dimension

| DQ Metric Code | Violation Rate | KQPI | Relevant Field(s) | Cluster | Weight (C:1) | Weight (C:2) (k=1) | Weight (C:3) (k=2) | Weight (C:4) (k=3) |
|---|---|---|---|---|---|---|---|---|
| **CNS1** | 0% | 10 | Client ID | C | 0,067 | 0,000 | 0,000 | 0,000 |
| **CNS2** | 0,01% | 9,999 | Tax ID | C | 0,067 | 0,000 | 0,000 | 0,000 |
| **CNS3** | 3,61% | 9,639 | Risk Cat. Code | B | 0,067 | 0,077 | 0,063 | 0,053 |
| **CNS4** | 3,61% | 9,639 | Risk Cat. Name | B | 0,067 | 0,077 | 0,063 | 0,053 |
| **CNS5** | 0% | 10 | Client Risk Class, Firm Segment | B | 0,067 | 0,077 | 0,063 | 0,053 |
| **CNS6** | 43,84% | 5,616 | Firm Segment, Firm Turnover | B | 0,067 | 0,077 | 0,063 | 0,053 |
| **CNS7** | 6,28% | 9,372 | Firm Segment, Firm Per. Number | B | 0,067 | 0,077 | 0,063 | 0,053 |
| **CNS8** | 38,31% | 6,169 | Firm Segment, Firm Asset Size | B | 0,067 | 0,077 | 0,063 | 0,053 |
| **CNS9** | 0% | 10 | Credit Type, CCF | A | 0,067 | 0,077 | 0,125 | 0,158 |
| **CNS10** | 87,68% | 1,232 | Collateral Type, Mortgage Value | A | 0,067 | 0,077 | 0,125 | 0,158 |
| **CNS11** | 87,68% | 1,232 | Collateral Type, Mortgage Degree | A | 0,067 | 0,077 | 0,125 | 0,158 |
| **CNS12** | 87,68% | 1,232 | Collateral Type, Mortgage No | B | 0,067 | 0,077 | 0,063 | 0,053 |
| **CNS13** | 87,68% | 1,232 | Collateral Type, Appr. Firm Name | B | 0,067 | 0,077 | 0,063 | 0,053 |
| **CNS14** | 87,68% | 1,232 | Collateral Type, Appr. Rep. Code | B | 0,067 | 0,077 | 0,063 | 0,053 |
| **CNS15** | 87,68% | 1,232 | Collateral Type, Last Appr. Date | B | 0,067 | 0,077 | 0,063 | 0,053 |

Since there is no field directly affecting credit risk calculation in KQPIs formed for uniqueness dimension, all weights are assumed to be equal for all the cases. Therefore, CQPIs yield the same result for all the cases. Due to application of this dimension to quite few fields which have good performance for uniqueness, CQPI results are close to perfect quality performance.

Increasing weights of the fields that are used as parameters in credit risk function and that have direct effect on those parameters improves the performance of CQPI of completeness. This is because overall quality performance of those fields is better than the remaining fields.

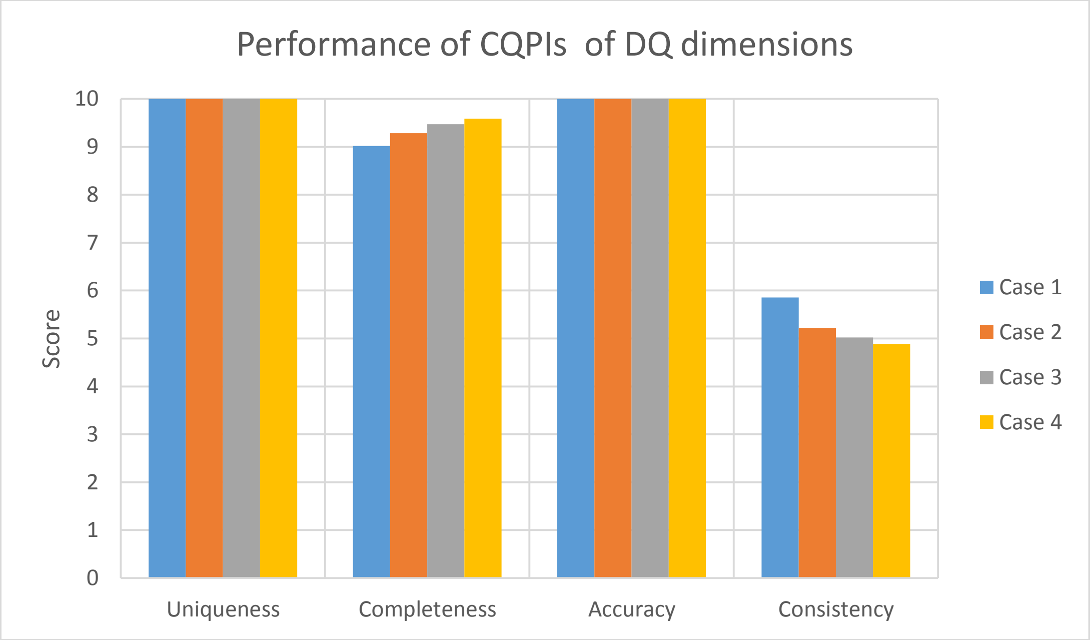
CQPI results are perfect for accuracy dimension for all the cases since there is no violation observed in this dimension.

The worst performance among the CQPIs is observed in consistency dimension. Scores of the CQPIs range between *5,86* and *4,88* under different cases. As the weights of the fields that are used as parameters in credit risk function and that have direct effect on those parameters are increased, we observe that the performance of the CQPIs falls since the weights of the fields that are significant for credit risk calculation and have poor performance on consistency.

**Table 30:** CQPI results of DQ dimensions for different cases of KQPI weights

| | **CQPIs** | | | |
|---|---|---|---|---|
| **DQ Dimensions** | ***Case 1*** | ***Case 2*** | ***Case 3*** | ***Case 4*** |
| Uniqueness | 10 | 10 | 10 | 10 |
| Completeness | 9,02 | 9,28 | 9,47 | 9,58 |
| Accuracy | 10 | 10 | 10 | 10 |
| Consistency | 5,86 | 5,22 | 5,02 | 4,88 |

Final quality performance results, i.e. CQPIs for the DQ dimensions for all four cases are given in Table 30 and are graphically presented in Figure 12. It can be clearly seen that quality performance of consistency dimension is well behind those of the other three DQ dimensions. Best quality performance belongs to accuracy and uniqueness dimensions and that of completeness is also fairly promising. As differentiation of weights among the fields by prioritization of the fields critical for credit risk calculation becomes more apparent, the CQPI for completeness dimension is lower while that for accuracy is higher.



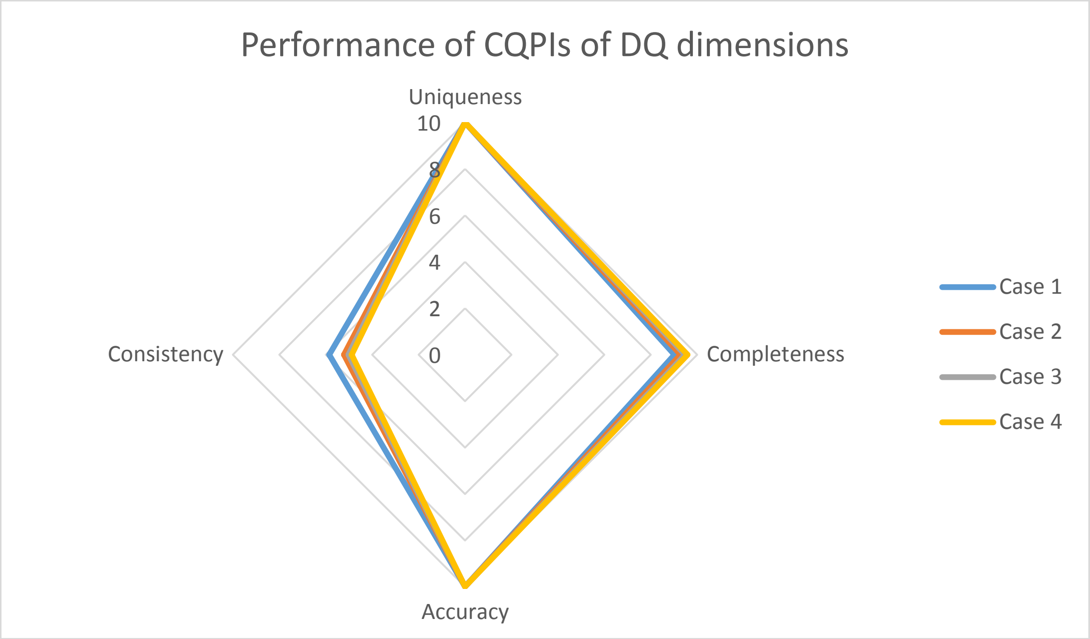


**Figure 12** Performance of CQPIs of DQ dimensions for different cases of KQPI weights

Designation of threshold values for DQA of the relevant DQ dimensions as proposed in Section 3.2.2.3 depends on the purpose of DQA and perception of criticality of the fields in concern. Criteria for setting threshold values for DQA of credit risk data can be based on subjective judgment and/or objective values.

### 4.2.3 Analysis of results of DQA for ABC Bank

The performance results of the DQ metrics provided in Section 4.2.2 can be analyzed to investigate the causes of poor DQ and underlying problems. We observe that the deterioration of DQ for relevant DQ dimension stems from poor and uncontrolled population of certain fields in various tables. Tax ID of both clients and warrantors reduces quality performance for various DQ dimensions. Unavailability of Tax IDs for considerable amount of clients causes such deterioration in uniqueness, completeness and consistency of data records belonging to all three tables. Risk Category Code and Risk Category Name fields existing in clients table also cause poor DQ for consistency and completeness. Unavailability and incorrect population of these fields deteriorates DQ in terms of completeness and consistency of these fields. Unavailability of firm information such as turnover, asset size and staff size for SMEs or corporates also causes inconsistencies among the fields; Firm Segment, Firm Turnover, Firm Asset Size and Firm Staff Size. Collaterals that are type of real estate also lack information about the real estate such as mortgage and appraisal information. Unavailability of Mortgage Value, Mortgage No, Mortgage Degree, Appraisal Firm Name, Appraisal Report Code and Last Appraisal Date for Collateral Type being real estate causes poor performance of DQ for consistency dimension. Thus, consistency performance of credit risk data is poor due to DQ problems in certain fields that have strong dependence on more than one field. Such dependence leads to spreading of DQ problems to the correlated fields, which reduces DQ performance with multiplicative effect.

ABC Bank was asked for an explanation regarding the problems confronted in the fields mentioned above. The bank has provided the outline of data collection and production process and explained the causes of deficiencies in satisfaction of DQ.

Production process of credit risk data of ABC bank is carried out through an application named “Credit Risk Management for Banking” (CRMB) embedded in a commercial software package used by the bank for credit risk management purposes. Raw data from the core banking software existing in the database of the bank were collected via Extract, Transform and Load (ETL) process and they were transferred to the database management system (DBMS). A second ETL process transforms these raw data to the format that can be used as input for the CRMB application. Processing of credit risk data in this application consists of four steps. These steps are:

1. ETL process – collection of raw data from DBMS, transformation of raw data to appropriate data format for CRMB application and determination of parameters rule sets for CRMB;
2. Matching credits with collaterals by using the new data format in accordance with rule set and calculation of ratios for credit risk management;
3. Formation of data tables via CRMB application that will be source for final outputs that contains results of credit risk calculation;
4. Production of final output tables for credit risk calculation in such a format that can be submitted to data transfer system of BRSA.

The current process of production and reporting of credit risk data summarized above is illustrated in APPENDIX C provided by the IT department of ABC Bank.

The underlying cause of the incompleteness and inconsistencies of the fields cited at the beginning of this section arises from the static nature of CRMB application which involves processes of creation, use and deletion of sophisticated data tables for credit risk calculation which prevent involvement of the users. Adaptation of the application for a new resulting data table format is very difficult due to prevention of such involvement. The final output table produced only contains risk calculation results in credit risk class level. When detailed report based on individual client, credit and/or collateral is desired; the application cannot provide data for all fields. Since temporary tables created for credit risk calculation in the third step are deleted after production of the resulting table, data belonging to certain fields cannot be accessed anymore. Thus, unavailability of data for those fields is mostly caused by ETL process which does not transfer input data to the resulting tables.

Another cause of the unavailability of those fields arises at the very beginning of data collection process from the clients. There is no well-integrated data collection system throughout the various branches of the bank. Data collected from the client by different branches are not systematically controlled while entering them into core banking software. Lack of such control leads to entrance of incomplete and inconsistent data.

### 4.2.4 DQ improvement actions for credit risk data of ABC Bank

Improvement techniques for DQ of a certain context depends on the nature of DQ problems that are revealed as a result of analysis of DQA results and investigation of causes of such problems as addressed in Section 3.2.3. Analysis of DQA results carried out in 4.2.3 reveals that there is a black box for the process of data transformation and credit risk calculation via matching credits of clients with collaterals of them, in which there is no possibility to monitor details of such transformation and matching and to manipulate temporary data tables created during the process. The process which is executed by CRMB application cannot provide some of the fields necessary for credit risk management and control due to loss or unavailability of transient data tables. Another revelation of the analysis is the lack of integrated data collection system for client information throughout the all units or branches of the core banking software of ABC Bank. Based on these findings, possible areas for improvement of quality of credit risk data are suggested as follows:

- As a short term solution, certain steps for process of production of credit risk data can be extracted from the black box so that the process of transformation of raw data and matching of credits with collaterals be more transparent and enable manipulation of data more easily. Challenges in implementing this solution may arise depending on ability of the bank to intervene the structure of the application due to complexity of codes and privacy concerns of the vendor. Since business rules imposed by the Basel framework for credit risk management are embedded in this application, the extent of intervention in the structure of the application would be limited.
- As a long term solution, in-house solutions can be developed which can relieve the bank from dependence on the vendors, which limit capability of the bank in processing data. A new investment for IT infrastructure due to such solution requires budget and time. Cost-benefit analysis of such analysis should be performed carefully. On the other hand, dynamic nature of the new system would enable the bank to ensure quality of its credit risk and adapt and implement new business rules more comfortably.
- Data collection should be performed more systematically. Roles, functions and responsibilities for the process must be defined clearly and distributed accordingly throughout the bank organization. Check points must be established for entrance of certain types of data that belong to clients in

different hierarchical levels so that errors caused by manual entry operations are minimized. Above all, the whole process should be integrated to the credit risk management system.

Implementation of some of the proposals outlined above will help the bank to achieve higher quality of its credit risk data which will enable the bank to accurately quantify, measure and calculate its risk exposure issues.

Since the author of the present study has been a member of the team of auditors for ABC Bank, the present method discussed in Chapter 3 was applied as described in Chapter 4 in the audit process during the period April 2015 – May 2015 in order to identify major DQ problems causing deficiencies in credit risk management. An action plan based on our findings reported May 2015 has been prepared by ABC officers in order to resolve the issues pointed out in the report. The action plan is focused mainly on reducing dependency on the software of the vendor which limits the capability of the bank in extracting and processing credit risk data. All four steps of the process of credit data production summarized in Section 4.2.3 are performed by the CRMB application of the software used in credit risk calculations while the action plan intends to internalize most of these steps (excluding Step 2 in which a calculation engine matches credits with collaterals optimally) rather than outsourcing to the vendor. The fundamental steps of the action plan are presented in APPENDIX D.

# CHAPTER 5

# VALIDATION OF THE DQA APPROACH

This chapter is devoted to assessing the applicability and validity of the DQA approach proposed by carrying out a comprehensive survey addressing numerous Turkish banks. The survey questionnaire (APPENDIX E) mainly consists of two parts and an appendix. The first part investigates ongoing data quality assessment activities within the banks surveyed and their understanding of the concept of data quality in credit risk management. The second part requests evaluation of the proposed approach by the banks' risk management seniors. The appendix presents the approach in order to help banks understand its details.

## 5.1 General information about the participants of the questionnaire

The questionnaire has been prepared and sent to 46 banks present in the sector; however, thirteen of those banks have responded to the survey. Some banks sent their apologies for not participating in the survey due to their lack of time arising from having to prepare end-of-year reports while some other banks sent their apologies stating that they, as risk management department, cannot individually respond to the questionnaire since it requires to involve participation of all stakeholders within the bank organization which would take very long time periods.

When we studied the participant profiles of the thirteen banks who participated, we observed that all participants were senior managers working within either risk management departments or equivalent units. Also, risk management departments of some banks have got support from IT departments or several other departments of their own banks as suggested by the questionnaire. Participant profiles of the banks surveyed are outlined in Table 31. Asset sizes and types of the banks are also provided in the table. Asset size of the banks is grouped under three classes. Class 'A' refers to those banks having asset size higher than 100 billion TL, Class 'B' refers to those banks having asset size between 10 billion TL and 100 billion TL, and Class C refers to those banks having asset size lower than 10 billion TL. The banks are of type either deposit or development and investment.

**Table 31** General information about the participants of the questionnaire

| *Bank No* | *Asset Size Group* | *Bank Type* | *Participant Title* | *Department/Unit* | *Experience (years)* |
|---|---|---|---|---|---|
| *Bank1* | A | Deposit | Basel II Validation Manager | Risk Management | 6 |
| *Bank2* | A | Deposit | Assist. Credit Risk Manager | Risk Management | 16 |
| *Bank3* | C | Development & Investment | Assistant Manager/ Assistant Manager | Risk Management/ Financial Control | 8/17 |
| *Bank4* | B | Deposit | Manager | Capital Management | 8 |
| *Bank5* | C | Deposit | Manager | Risk Management | 17 |
| *Bank6* | B | Deposit | Manager/ Senior Engineer | Credit Risk Analytics & Capital Management/ IT | 15/? |
| *Bank7* | B | Deposit | Manager | Risk Management | 20 |
| *Bank8* | B | Deposit | Manager | Risk Management | 17 |
| *Bank9* | C | Development & Investment | (Risk) Manager/ (Credit Risk) Manager | Risk Management | 16/12 |
| *Bank10* | C | Deposit | Manager | Risk Management | 15 |
| *Bank11* | C | Development & Investment | Manager | Risk Management | 20 |
| *Bank12* | B | Deposit | Manager | Risk Weighted Asset Reporting | 13 |
| *Bank13* | C | Deposit | Competent | Risk Management | 27 |
| | | | | **Average** | **15,9** |

## 5.2 Findings of the Questionnaire

This section will present the findings of the questionnaire which inquires both ongoing data quality activities within the banks and evaluation of the banks towards our proposed approach.

### 5.2.1 Data Quality Assessment Activities within the Banks

The findings of the part of the survey that inquires ongoing data quality assessment within the banks are provided in this section.

All surveyed banks except one consider that there should somewhat exist a specific approach or method in order to assess quality of credit risk. As Figure 13 indicates, most banks agree that there is a significant need for a specific approach.

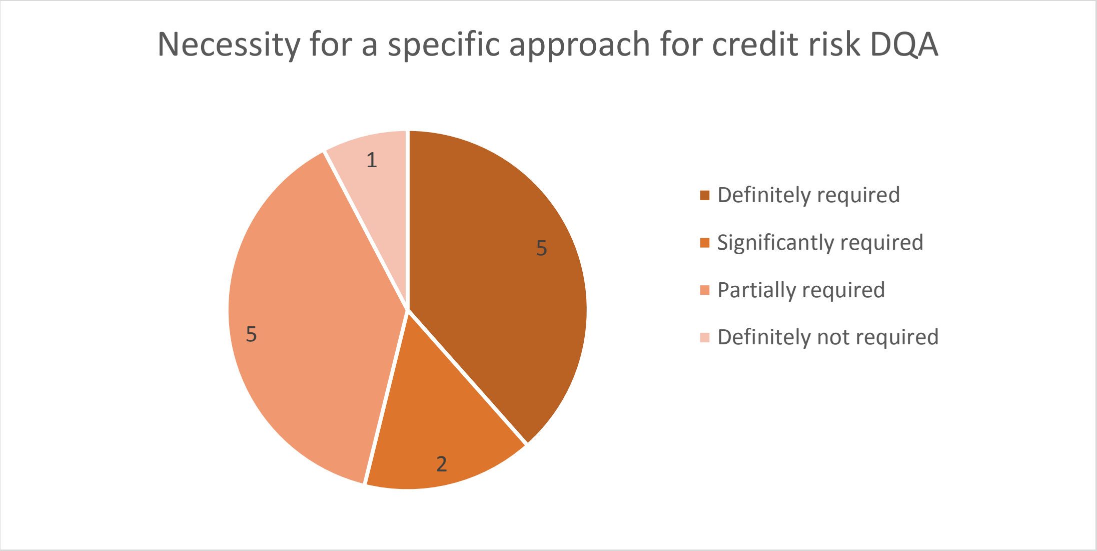


**Figure 13** Banks' view on necessity for a specific approach for credit risk DQA

Only one of the banks stated that there is no any ongoing DQA activity performed in credit risk management of the bank as shown in Figure 14.

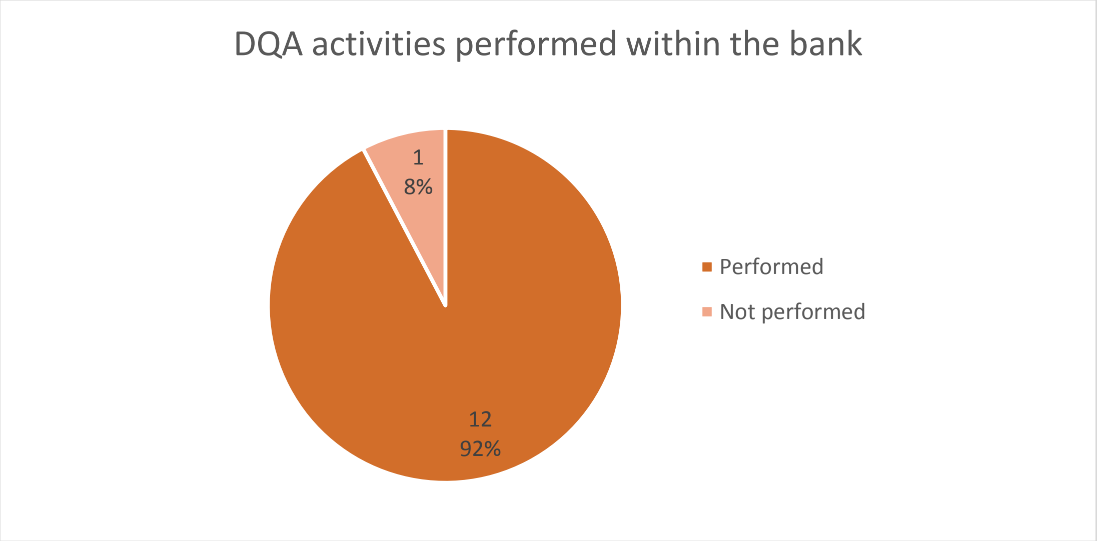


**Figure 14** Banks performing DQA activities in credit risk management

In order to understand which activities in data quality assessment process are performed by the banks, participants are inquired as to whether they perform activities similar to the ones defined in our approach. The responses are depicted in Figure 15.

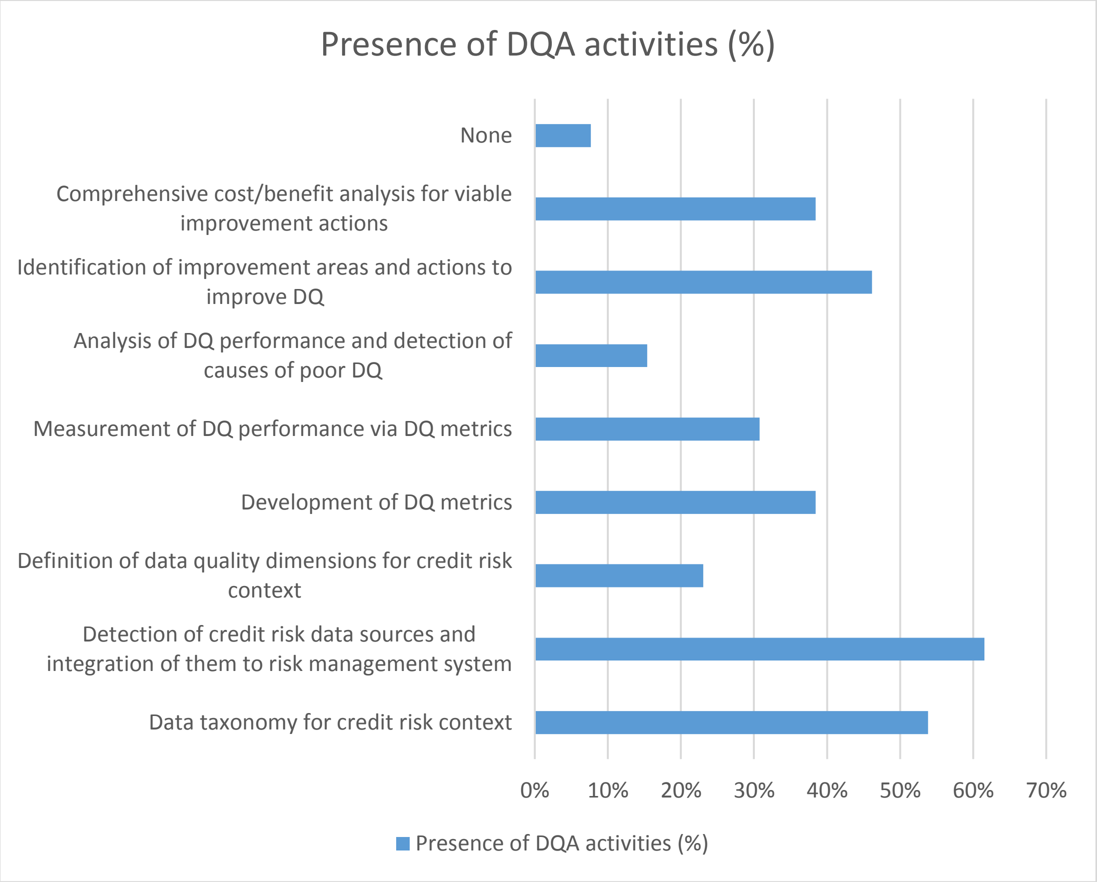


**Figure 15** Data quality assessment activities performed by the banks

The activity mostly performed by banks is identification of credit risk data sources and its integration to the risk management system. Other most performed activities are definition of data taxonomies and identification of improvement areas with viable actions. On the other hand, the least performed activity is analysis of DQ performance and detection of causes of DQ problems. One of the banks does not perform any activity listed in our survey.

Data quality assessment methods of banks are observed to include both qualitative and quantitative elements. Self-evaluation results of their DQA methods by the banks in terms of quantitativeness versus qualitativeness are given in Figure 16. There is no bank that applies purely quantitative assessment method. On the other hand, there is one bank that performs the assessment purely on a qualitative basis. We observe that DQA methods of the banks are evenly distributed in being whether they tend to be more quantitative or qualitative.

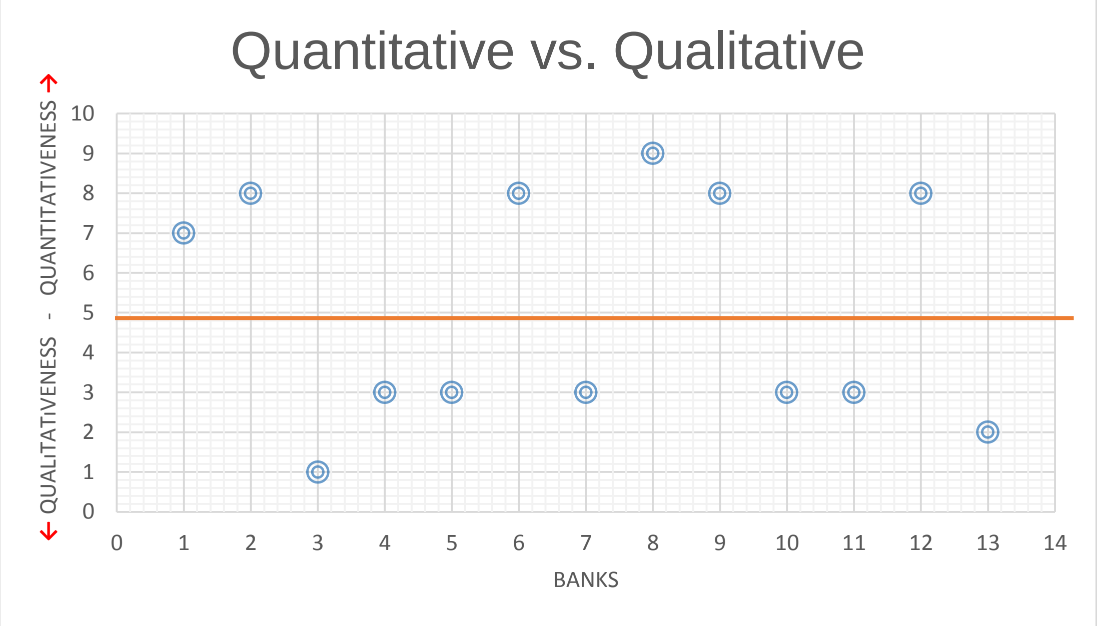


**Figure 16** Quantitativeness versus Qualitativeness of DQA methods used by the banks

Our approach has identified four main data categories one of which is derived from the other three as described in Section 3.2.1.1. Those categories contain final data that are used in credit risk management and more specifically credit risk calculation. The banks participating in the survey were also inquired as to which categories they use in their credit risk management practices. The responses are presented in Table 32.

**Table 32** Classification of credit risk data by the banks

| ***Bank No*** | **Classification of Credit Risk Data** |
|---|---|
| *Bank1* | Clients, Credits (including collaterals), Parameter tables (CCF, classification etc.), Rating tables based on credit/client |
| *Bank2* | Clients, Credit Cards, Derivative transactions, Personal loans, Commercial loans, Collaterals |
| *Bank3* | Credits, Collaterals, Repos, Derivative financial instruments, Securities portfolio, Clients-trial balance |
| *Bank4* | Clients, Credits, Collaterals, Client groups, Rating grades, Scorecards |
| *Bank5* | Clients, Credits, Collaterals, Trial balance, Country ratings |
| *Bank6* | Clients, Credits, Collaterals |
| *Bank7* | Clients, Credits, Collaterals, Rating system, Approving authorities |
| *Bank8* | Clients, Credit type (cash/non-cash), Interest type (fixed/variable), Collaterals |
| *Bank9* | Clients, Credits, Collaterals, Client/firm group information, Risk classes, Client types, Non-performing loans |
| *Bank10* | Clients, Credit types (cash/non-cash), Collateral types |
| *Bank11* | Clients, Credits, Transaction type, Client groups |
| *Bank12* | All details of the clients based the account number |
| *Bank13* | Clients, Credits, Collaterals, Limits |

The categories presented by the banks demonstrate considerable variation. Although almost all banks have distinct tables for clients, credits and collaterals; there are additional tables used in credit risk management. Certain banks have divided their transactions into different tables such as personal loans, commercial loans, derivatives, securities portfolio and repos. Several banks count rating system under one of the categories. Some banks have created distinct tables for identifying client groups. We infer that banks can categorize their credit risk data based on their portfolio content. Our approach combines most of the distinct tables of the banks in a number of data categories. There is also a different perspective between the data taxonomy of our approach and those of the banks in that they also contain data tables which are considered under supplementary system in our approach. Rating system, parameter tables and trial balance can be given as examples.

Our approach has determined four supplementary systems that feed data to risk management system in the definition phase of the approach in Section 3.2.1.2. Those are account management system, accounting system, collateral management system and rating system. Use rates of those systems obtained from the survey questionnaire are provided in Figure 17. Survey findings indicate that accounting system is used by all banks as expected. Other systems mostly used as data source for risk management system are account management system and collateral management system. Near half of the banks use data obtained from their rating system. There are certain banks that use additional data sources different than the systems identified by the approach we have proposed. Two banks state that they also gather information from "core banking system". This system is the software used to support most common transactions of banks such as managing accounts, loans, deposits and payments. In other words, it contains some of the systems proposed by the approach and it integrates them with an interface. One bank uses an additional system for non-performing loans.

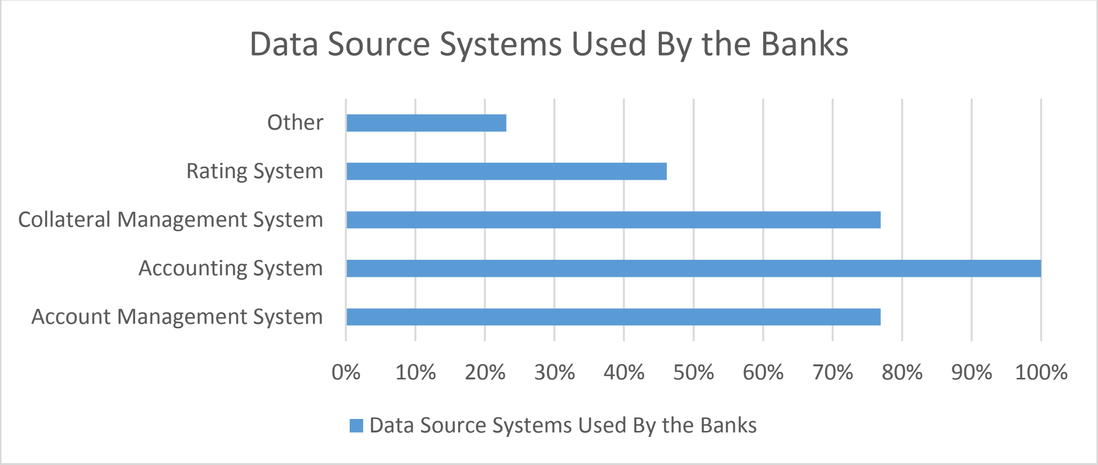


**Figure 17** Data source systems used by the banks

Our approach has defined five data quality dimensions in the definition phase of the approach in Section 3.2.1.3. Those data quality dimensions are completeness, uniqueness, consistency, accuracy and timeliness. Use rate of those dimensions obtained from survey results are provided in Figure 18. Survey findings show that the majority of banks use all of those dimensions in their data quality assessment activities. All banks surveyed use accuracy and consistency dimensions. One bank uses a data quality dimension other than those defined in our approach. This dimension is “coherence” which is defined by the bank as conformance to reference data set (data from external tables).

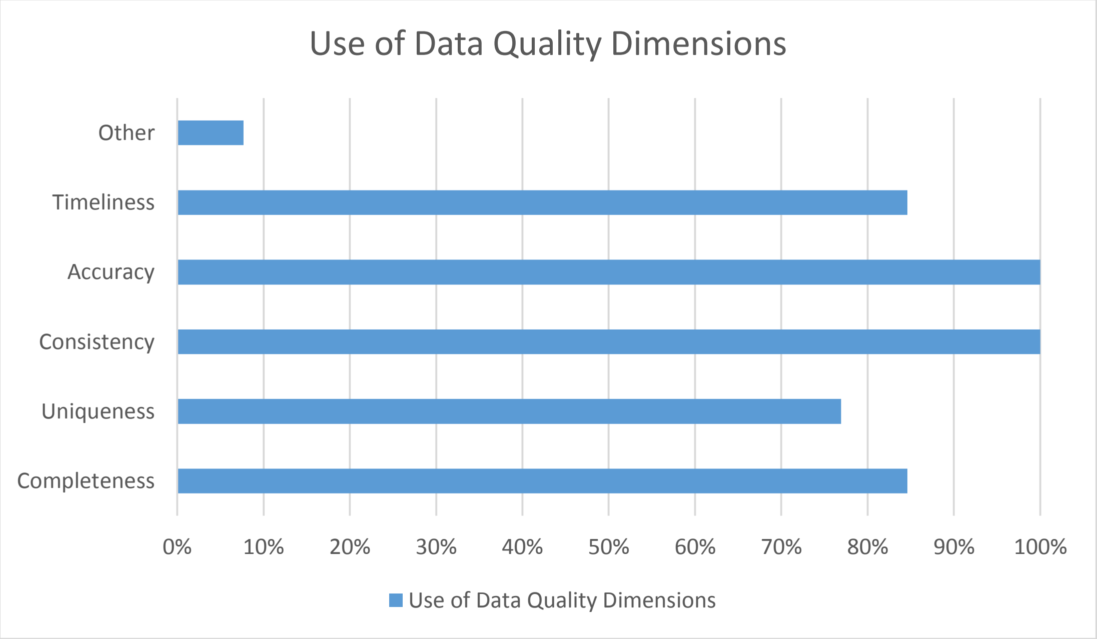


**Figure 18** Use of data quality dimensions across the banks

Survey findings show that 5 out of the 13 participating banks use data quality metrics in order to measure data quality performance for given data quality dimension. That implies it is ambiguous what majority of banks use as reference in order to perform DQA.

DQA methods that can be used to measure the performance of the metrics created have been given in Section 3.2.2.2. Banks were asked to provide which DQM methods they were using in their quality assessment of credit risk data. Findings are provided in Figure 19. The most commonly used method is data validation. The next commonly used method is column analysis. About half of the responding banks also use semantic profiling, domain analysis, cross-domain analysis and primary key/foreign key analysis. Schema matching and matching algorithms are the less commonly used methods by the banks. One bank also uses a method referred as “Trend Analysis”. This method is used by the bank instead of matching algorithms in order to identify duplicate values.

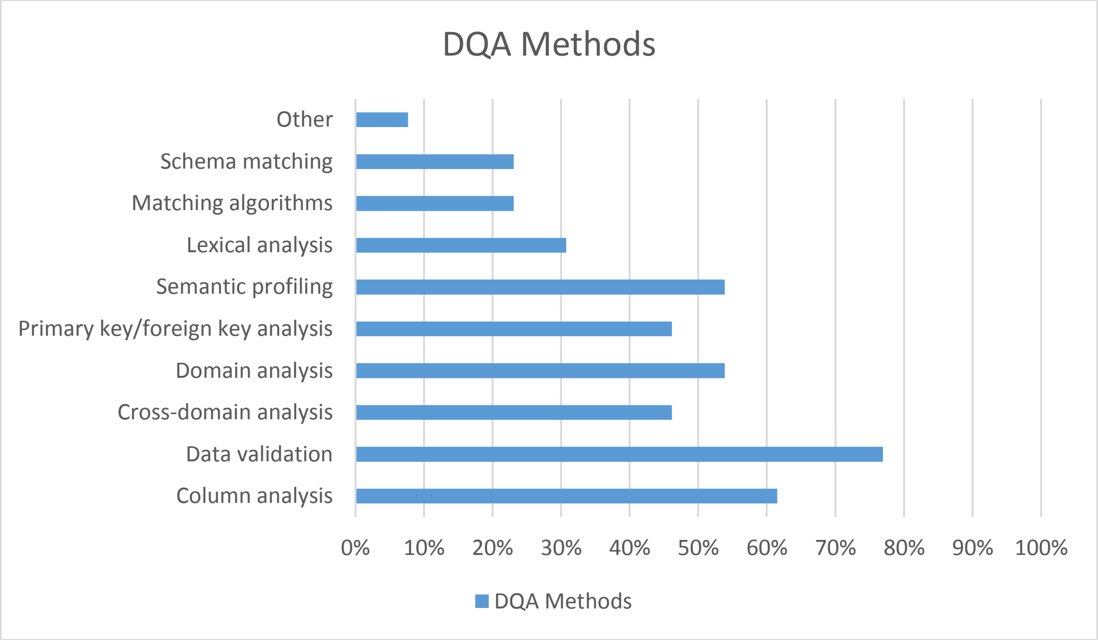


**Figure 19** DQA methods that are used by the banks

Eight of the banks state that they prioritize data types used in credit risk management since they consider that certain data types are critical for credit risk management.

When banks are asked to state the purpose why they are performing DQA according to their priority for credit risk management, great majority of them put allocating accurate capital by calculating credit risk accurately at first place as shown in Figure 20. One bank considers it is the second most important purpose while another bank puts it at third place in DQA in credit risk. In addition, all the banks surveyed view this purpose among the first three ones. Majority of banks consider verifying quality of data obtained from other data sources via IS infrastructure to be the second most significant purpose in DQA in credit risk while some banks put it at third place and some banks do not view it as one of the most important purposes of DQA. More than half of the banks have stated that ensuring reliability of data used in credit risk management as input for credit risk calculations is the third most significant purpose in their DQA practices while a bank considers it as the most desired purpose for performing DQA and certain banks consider its importance at second place. One bank has also additional purposes for DQA other than the choices provided in the questionnaire. The bank states that the most important purpose of DQA is to ensure the rating systems of the bank make the right decisions in such areas as credit allocation and monitoring, budget planning, risk appetite.

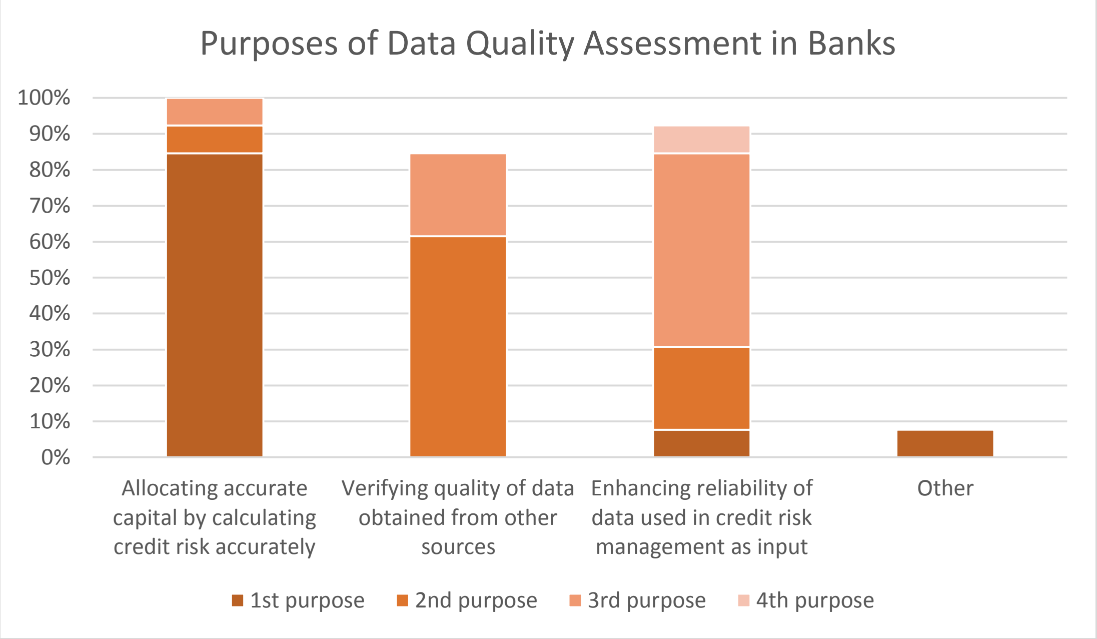


**Figure 20** Precedence of purposes of data quality assessment across the banks

Survey findings indicate that the most frequently encountered problems are missing data values and duplicate records. About half of the banks surveyed have stated that they experience those data quality problems. The least commonly encountered problem has come out as data values violating domain constraints. On the other hand, about one third of the banks state that they do not experience any data quality problem.

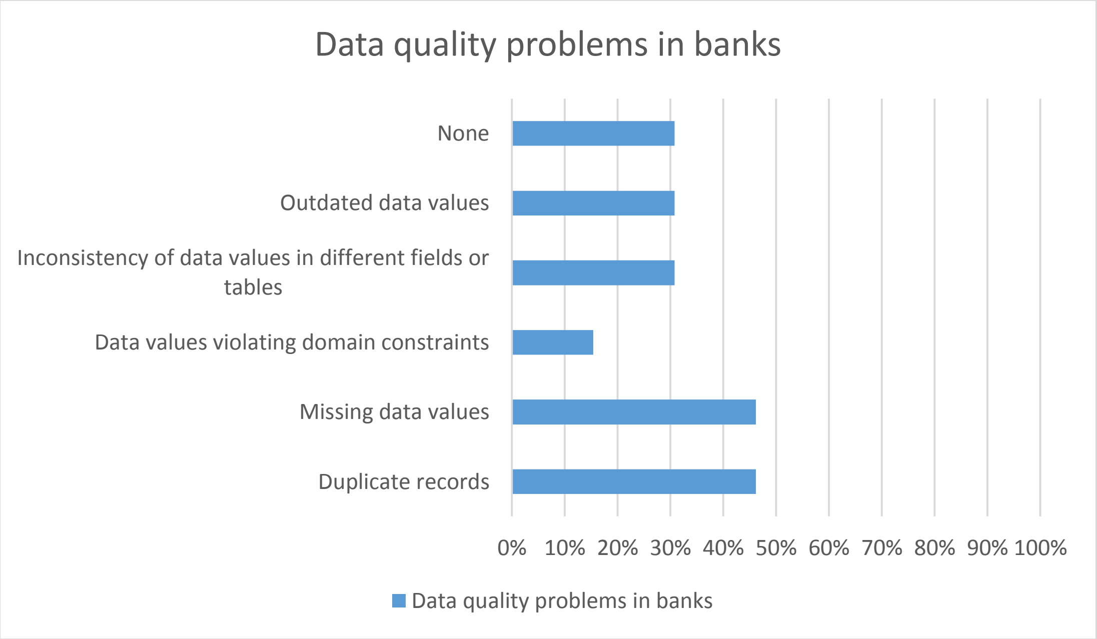


**Figure 21** Data quality problems experienced by the banks

Inquiring the causes of those data quality problems, the findings presented in Figure 22 have been obtained. The most critical cause of the problems is suggested as manual data entry. Majority of the banks view this cause as critical. The next most critical causes are observed to be consolidation of data from multiple tables and inability to update data simultaneously in all relevant tables. Other than lack of central database, all other causes suggested in the questionnaire are somewhat experienced by the banks surveyed. On the other hand, three banks out of thirteen banks surveyed have stated that none of the causes provided are encountered in their data quality management activities.

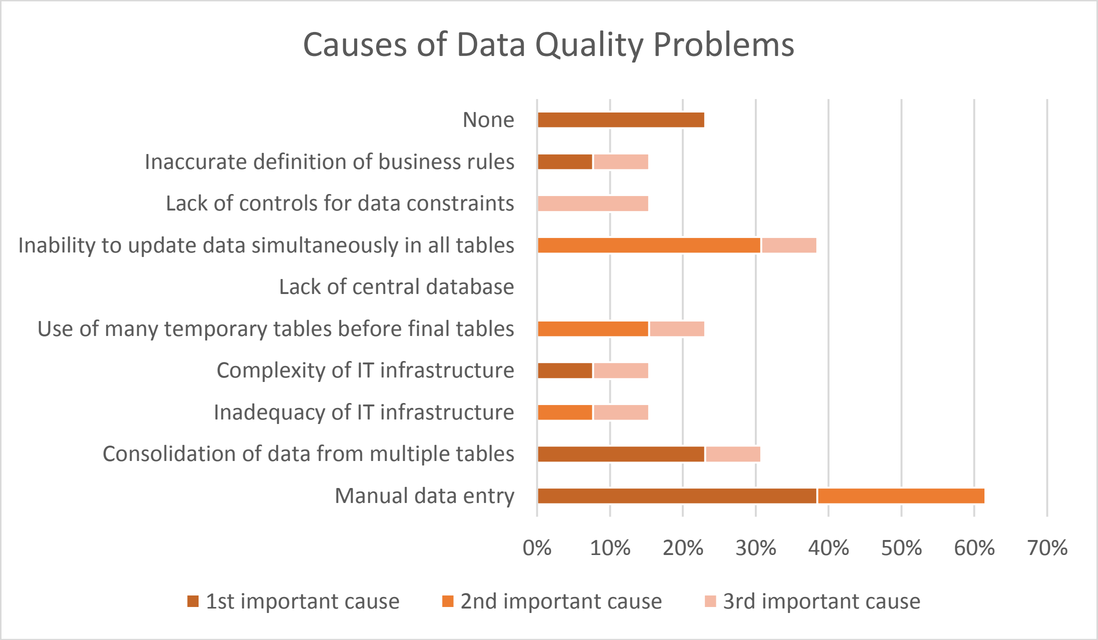


**Figure 22** The causes of data quality problems experienced by the banks

The banks surveyed stated that they have already applied improvement methods to some extent in order to solve data quality issues they faced as shown in Figure 23. About half of the banks have implemented solutions that have changed IT infrastructure significantly. Others have implemented solutions that have partly changed IT infrastructure or that are patch solutions not affecting IT infrastructure significantly. On the other hand, two banks have expressed that there has been no improvement activity performed.

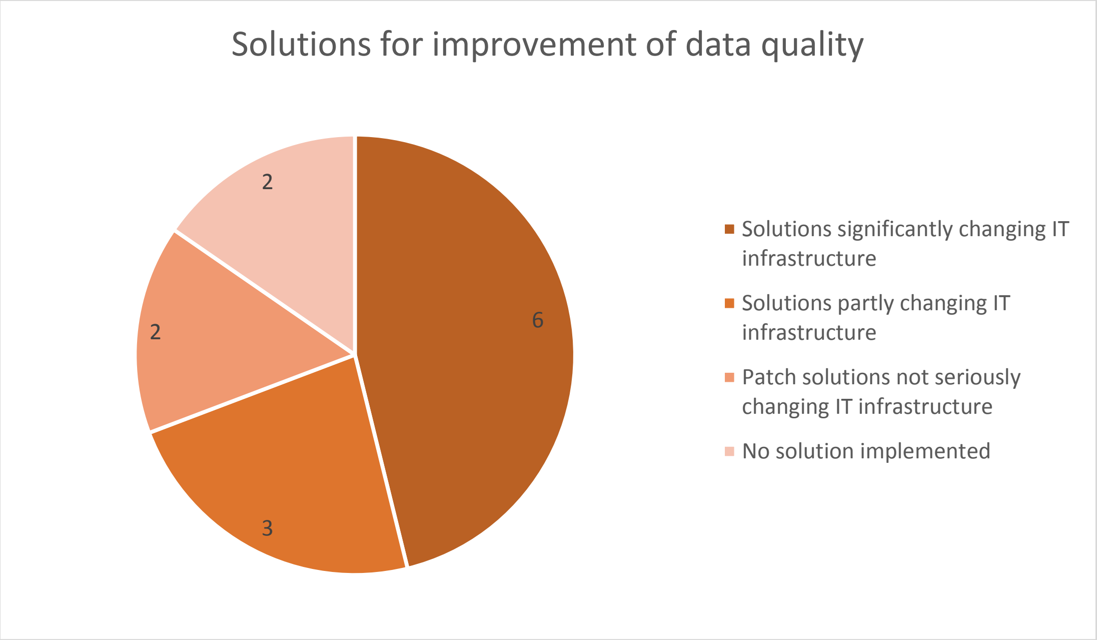


**Figure 23** Solutions for improvement of data quality performed by the banks

When banks were inquired as to the criteria they take into consideration in selecting methods for improvement of data quality, they point out that they focus more on legal applicability of the method as indicated in Figure 24. Costs, benefits and practical applicability of the method are the other most favored criteria for the banks surveyed. The least favored criterion is acceptance of the method within the bank. One bank does not state any selection criterion since it does not use any improvement method.

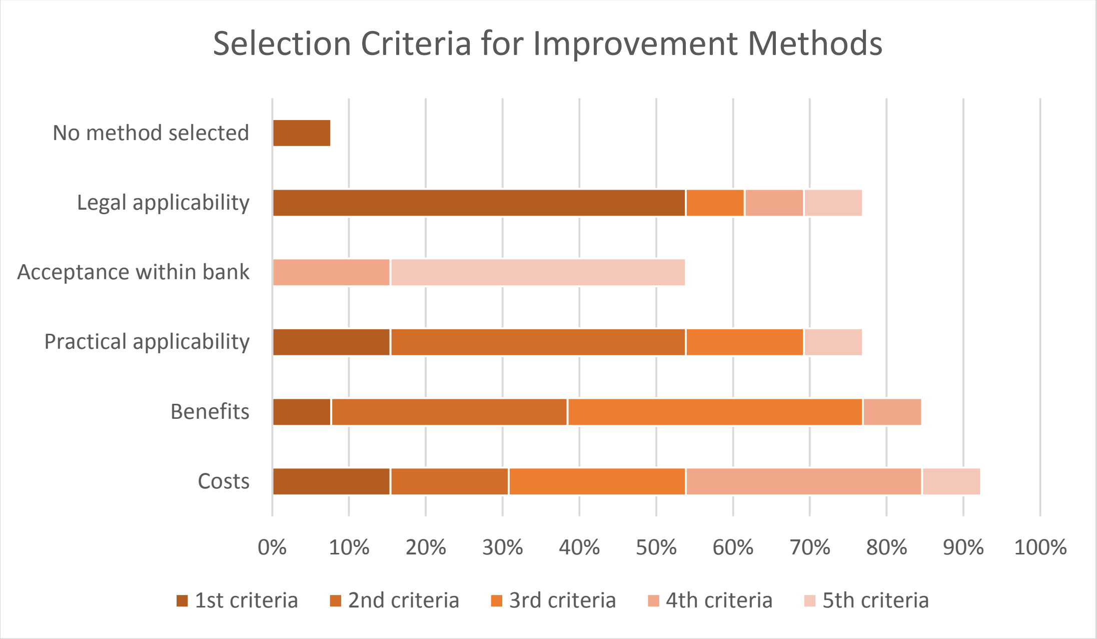


**Figure 24** Selection criteria for methods of data quality improvement

The banks were also asked to evaluate satisfactoriness of their own DQA activities, responses to which are shown in Figure 25. The average of the self-evaluation has is *7,7* out of *10*. Two banks consider that their DQA process is completely satisfactory. Only one bank has distinctive evaluation stating that their DQA process is not quite satisfactory.

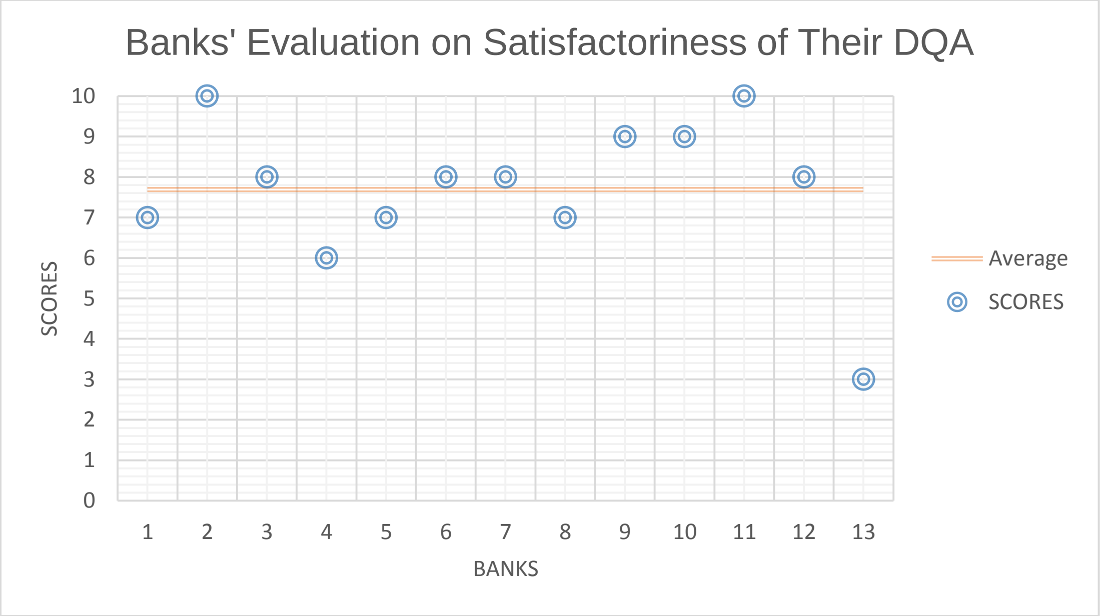


**Figure 25** Self-evaluation of the banks on their DQA activities

### 5.2.2 Evaluation of the Banks regarding the Proposed Approach

The results of the part of the survey that asked the banks to evaluate the approach proposed by the present study are provided in this section.

The data taxonomy for credit risk has been created in the definition phase of the approach proposed in Section 3.2.1.1. The banks were asked to evaluate sufficiency of the taxonomy. All banks participating in the survey view the data taxonomy sufficient for data quality management practices in credit risk management. Two of those banks consider that it is very sufficient.

Entities and their relevant attributes under the data taxonomy suggested for credit risk context by the approach in Section 3.2.1.1 were presented to the banks in the questionnaire so that they grade them according to their significance for credit risk management. The highest significance score is **[1]** and the lowest significance level is **[5]** in the survey question. Averages of the scores given by the banks are presented for each attribute of given entity in Table 33. Those average scores are also reflected to radar plots shown in Figure 26 by transforming the values in order to interpret on the radar graph more meaningfully. The transformation is made by linearly mapping the highest significance to **[1]** and the lowest significance value to **[0]** as follows:

*Transformed Score* = (5 + 1 – *Untransformed Score*) / 5

The banks have rated all the attributes defined for the data entities under credit risk context as over a certain significance level (the arithmetic average of all significance levels from **[1]** to **[5]**). Therefore, they view each of the attributes considerably significant for credit risk management based on the average scores assigned by the banks.

The most significant obligor attribute is risk group of the obligor on the average according to the banks. On the other hand, the least significant obligor attribute seems to be obligor identity. Transaction amount appears to be the most significant attribute of transaction entity on the average while accounting record is viewed as the least significant attribute according to the banks' responses. The banks consider the type of credit protects as the most significant attribute of credit protection entity whereas the identity (ID number) of credit protection is regarded as the least significant attribute. Allocated protection amount and risk weighted exposure after credit risk mitigation are the most significant attributes for credit risk management while obligor identity attribute of the relationship entity, credit risk function, is the least significant one according to the banks evaluation.

**Table 33** Average of scores assigned by the banks to the importance of the proposed attributes of credit risk data entities by the banks

| *Entity* | *Attribute* | *Average Importance (1-highest, 5-lowest)* |
|---|---|---|
| *Obligors* | Obligor Identity | 2,69 |
| | Obligor Type | 2,00 |
| | Financial Statement (for firms) | 1,62 |
| | Staff Size (for firms) | 2,69 |
| | Obligor Credibility (rating) | 1,62 |
| | Risk Group | 1,54 |
| *Transactions* | Transaction Identity | 2,15 |
| | Accounting Record | 2,38 |
| | Transaction Type | 1,46 |
| | Credit Conversion Factor | 1,38 |
| | Transaction Amount | 1,15 |
| | Transaction Return | 2,31 |
| | Provisions/Losses | 1,31 |
| | Transaction Maturity | 1,46 |
| | Transaction Currency | 1,77 |
| *Credit Protections* | Credit Protection Identity | 2,23 |
| | Protection Type | 1,00 |
| | Protection Amount | 1,08 |
| | Protection Maturity | 1,54 |
| | Protection Rating | 1,54 |
| | Protection Currency | 1,62 |
| *Credit Risk Function* | Obligor Identity | 1,92 |
| | Transaction Identity | 1,85 |
| | Protection Identity | 1,69 |
| | Final Rating (after match) | 1,77 |
| | Exposure Before CRM | 1,15 |
| | Allocated Protection Amount | 1,08 |
| | Risk Weighted Exposure After CRM | 1,08 |

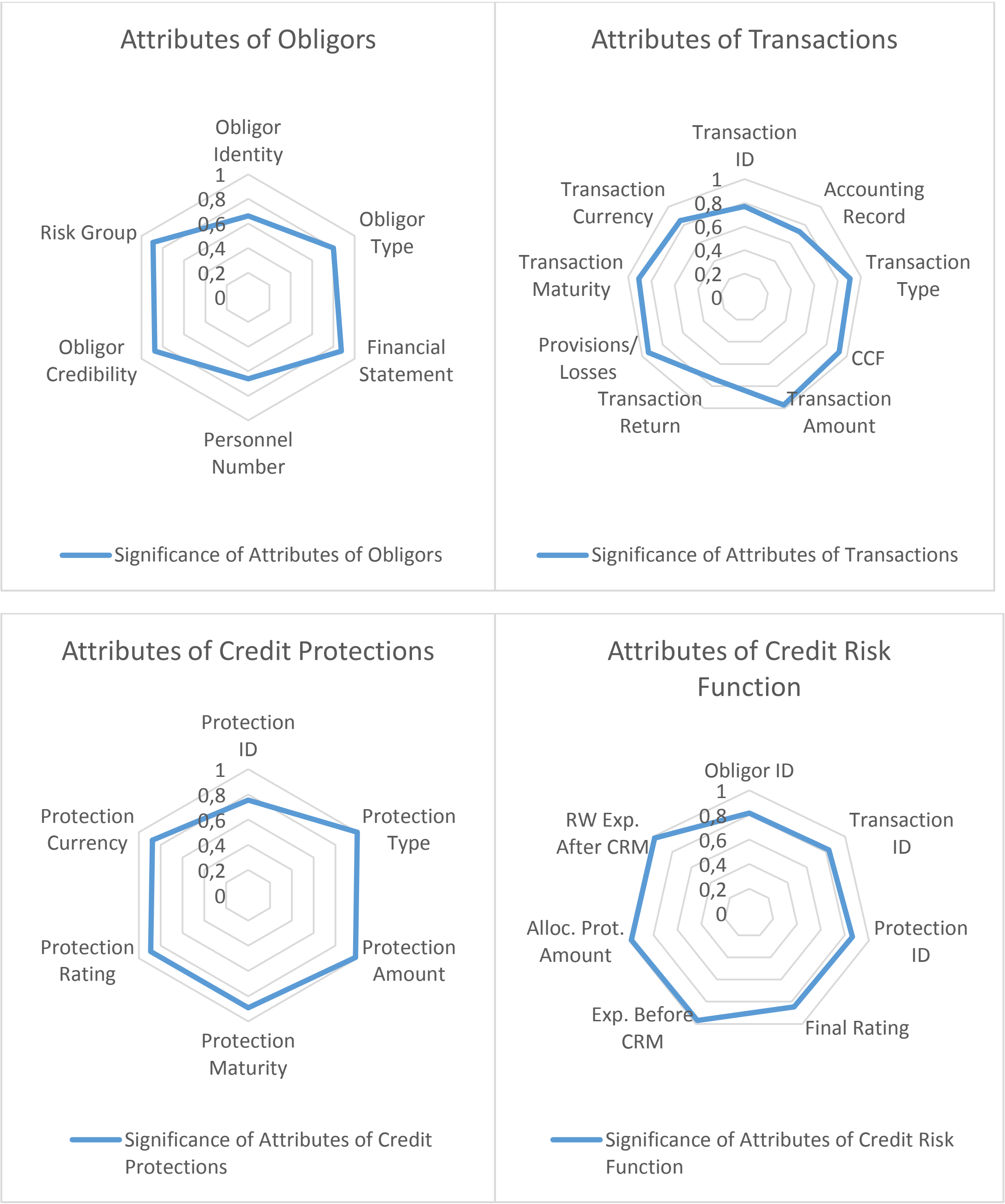


**Figure 26** Significance of attributes of credit risk data entities (obligors, transactions, credit protections and credit risk function) assigned by the banks

The supplementary systems that are used as data source of risk management system have been defined in Section 3.2.1.2. The banks were invited to evaluate appropriateness, i.e. comprehensiveness and modularity of those systems in terms of risk management. Averages of scores assigned by the banks are reflected in radar plots shown Figure 27. The banks find all systems defined by the approach remarkably appropriate overall. The most appropriate system seems to be accounting system followed by risk management system while the least appropriate system appears to be rating system according to the banks.

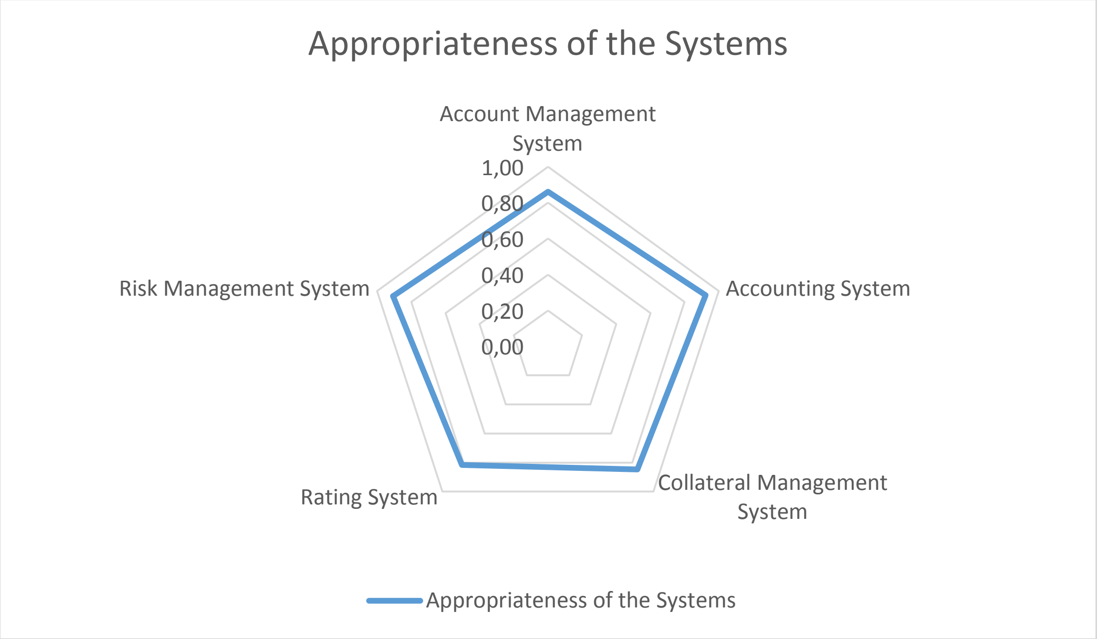


**Figure 27** Evaluation of the banks on appropriateness (comprehensiveness and modularity) of the systems defined for credit risk management

Except one bank all banks consider that adequacy of the proposed systems used to supply data to risk management system are satisfactory. Only one bank has responded that it is not satisfactory since a supplementary system is required. That is, there should be a special and comprehensive system for non-performing (past due) loans.

The banks surveyed were invited to evaluate relevancy of DQ dimensions which are defined and used in the definition phase of the approach in Section 3.2.1.3. The results of the evaluation are shown in Figure 28 as a radar graph formed by average of the scores submitted by the banks. The banks view all the DQ dimensions as relevant to credit risk management. The highest relevancy is attributed to accuracy and timeliness dimensions by the banks although other dimensions are also considered significant.

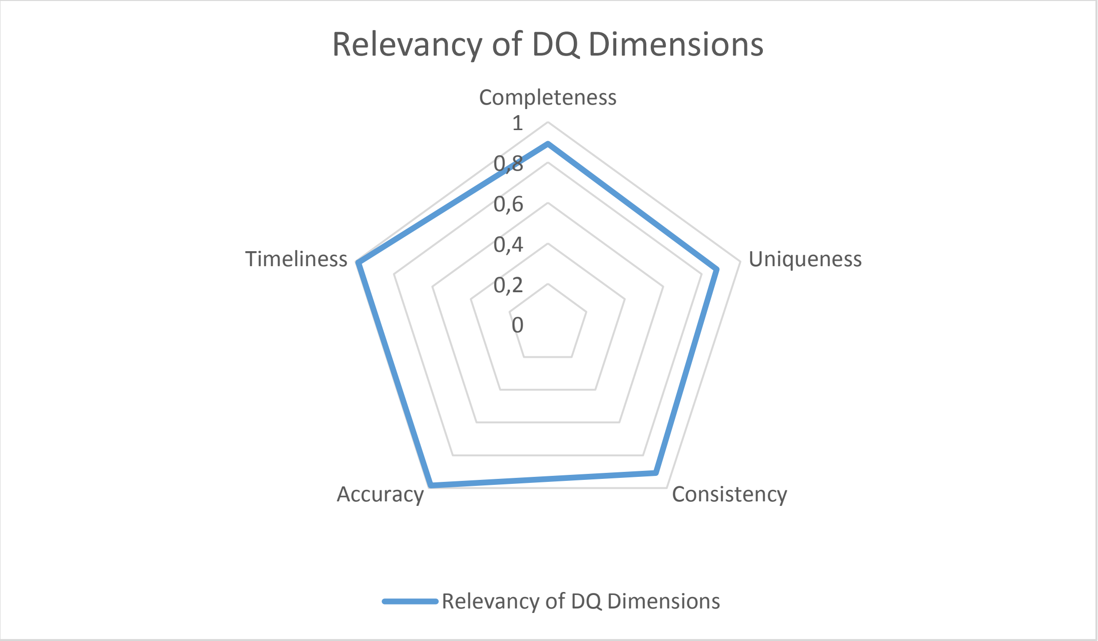


**Figure 28** Evaluation of the banks on relevancy of the DQ dimensions suggested by the approach

In addition, all the banks surveyed agree that the DQ dimensions suggested by the approach are satisfactory in overall in terms of data quality activities within credit risk management.

When asked about the contribution of the DQ metrics developed in the measurement phase of the approach to DQA practices and credit risk management, nine banks consider that significant contribution can be made while the remaining four banks have stated the opinion that there is partial contribution. No bank has pointed out uselessness of the DQ metrics.

Eight banks have stated that use of DQA techniques outlined in Section 3.2.2.2 and corresponding SQL queries created in the measurement phase of the approach are significantly effective on DQA process while the remaining five banks think that it has partial effect on the process. No bank has pointed out ineffectiveness of the DQA techniques.

Nine of the banks surveyed have stated that composite indicators which are derived from individual indicators in Section 3.2.2.3 are good representatives in the measurement of data quality performance for given dimension. Others are of the opinion that individual indicators would be solely better indicators or different kind of indicators could be developed.

The banks were asked about their opinion on how weights of each individual indicator for a given DQ dimension should be determined. Majority of them consider that they should be prioritized according to their significance for credit risk calculation while certain banks have stated that they can be changed depending on changes in credit risk management functions as shown in Figure 29.

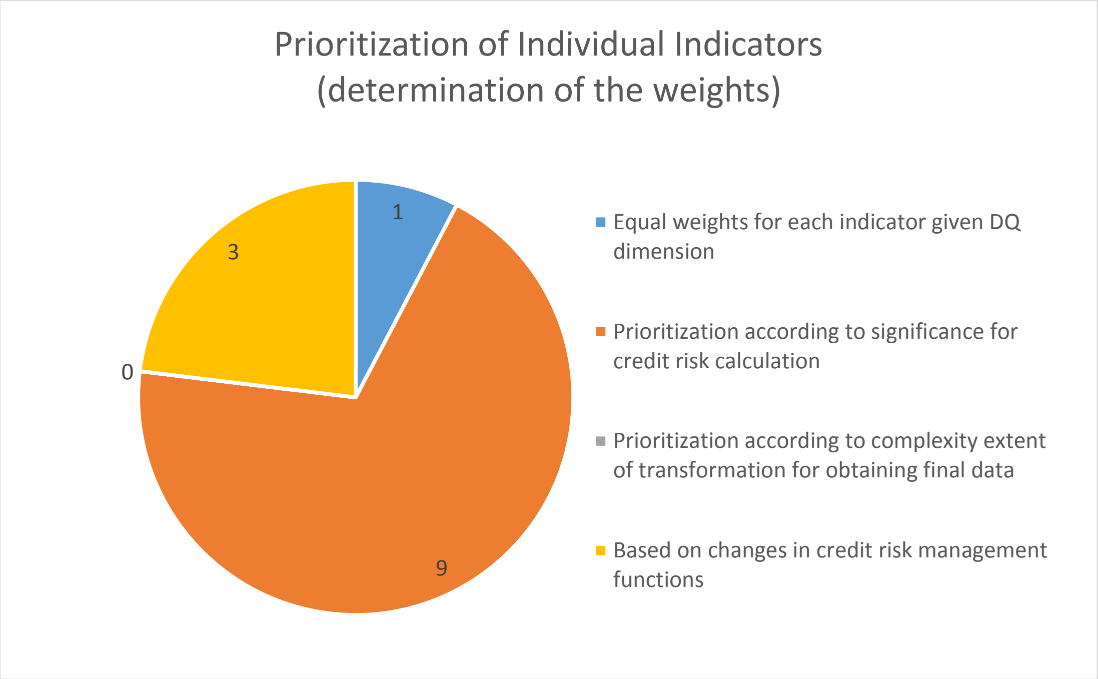


**Figure 29** Evaluation of the banks on prioritization of individual indicator, i.e. determination of their weights

Only one bank has stated that equal weights should be attributed to each individual indicator. Furthermore, no bank considers that they should be prioritized according to the complexity extent of transformation that raw data of the attribute are exposed in derivation of final data.

More than half of the banks expect to detect DQ issues related to inconsistency of data values in different fields or tables in the analysis phase of the approach if they were to implement the approach proposed within their data quality management process according to the survey results of which provided in Figure 30. The next DQ issue to be addressed by the approach is expected to be missing data values according to slightly less than half of the banks. Duplicate records are also expected to be detected by the approach according to considerable number of the banks. On the other hand, three banks are of the opinion that there would be no DQ issue to be detected by the approach proposed if they were to apply it.

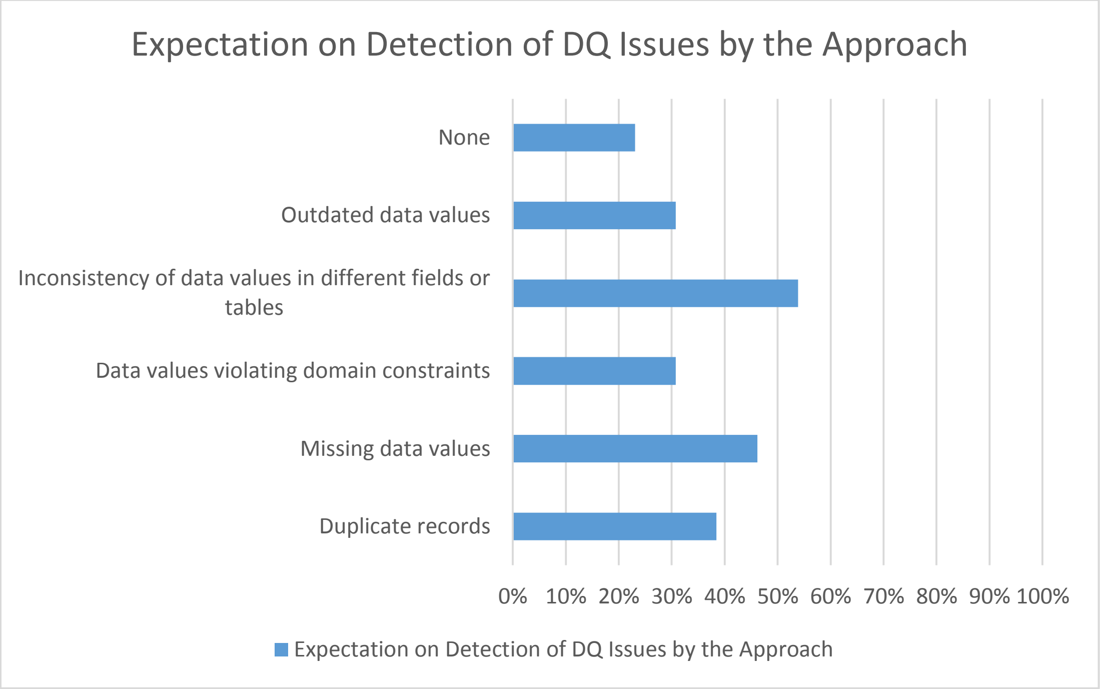


**Figure 30** Expectations of the banks on detection of DQ issues by the approach proposed

Ten banks have stated that they would prefer to select improvement techniques based on both their benefits and costs in the improvement phase if they were to use the approach according to the results of the survey. On the other hand, about quarter of the banks would prefer to make selection of the techniques based on only their benefits no matter how much they cost. Note that no bank is willing to make selection based on only cost figures.

When the banks were asked if they would like to use the approach proposed, near half of them stated that they would partially use it since it could beneficial for them while the rest of the banks stated that they would not use the approach as shown in Figure 31. Most of the banks that would not like to use the approach state that they do not require it since they do not encounter any DQ problems while the rest of non-users think that it will fail to address their DQ issues.

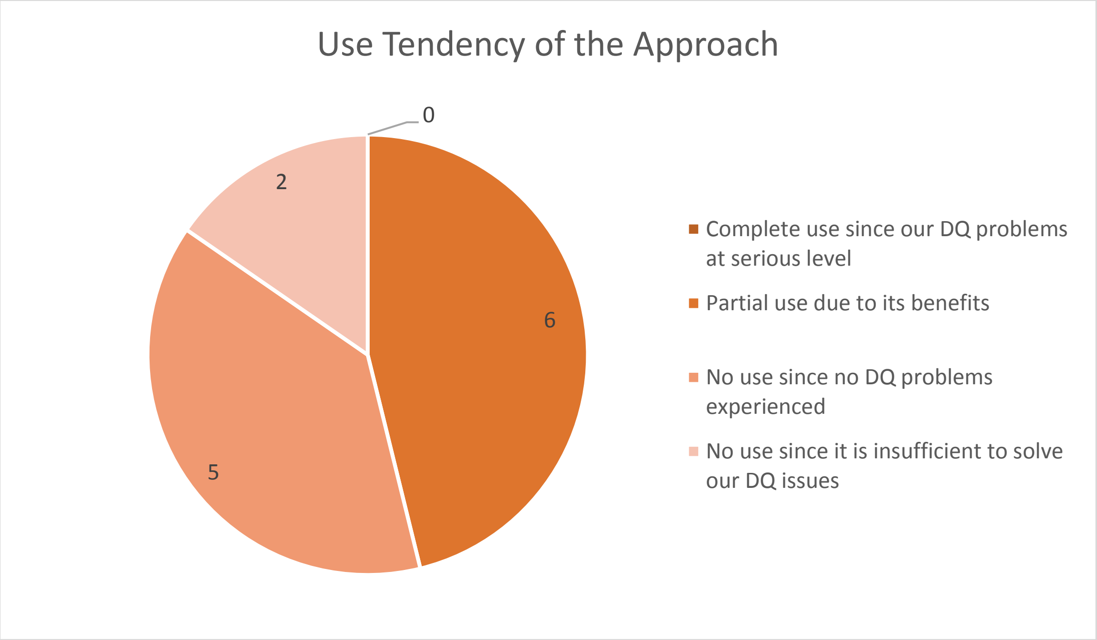


**Figure 31** Banks' use tendency of the approach proposed

The banks were asked to what extent they would rely on the findings of the approach if they used the approach and obtain certain results based on performance of the metrics of the approach. Twelve banks think that they could rely on the findings to some extent and they would consider them in data quality improvement while only one bank is willing to use with no doubt and plan actions for data quality improvement based on the evaluation of the findings according to the survey results. Note that no bank has stated that it would completely reject using the proposed approach due to unreliability to its results.

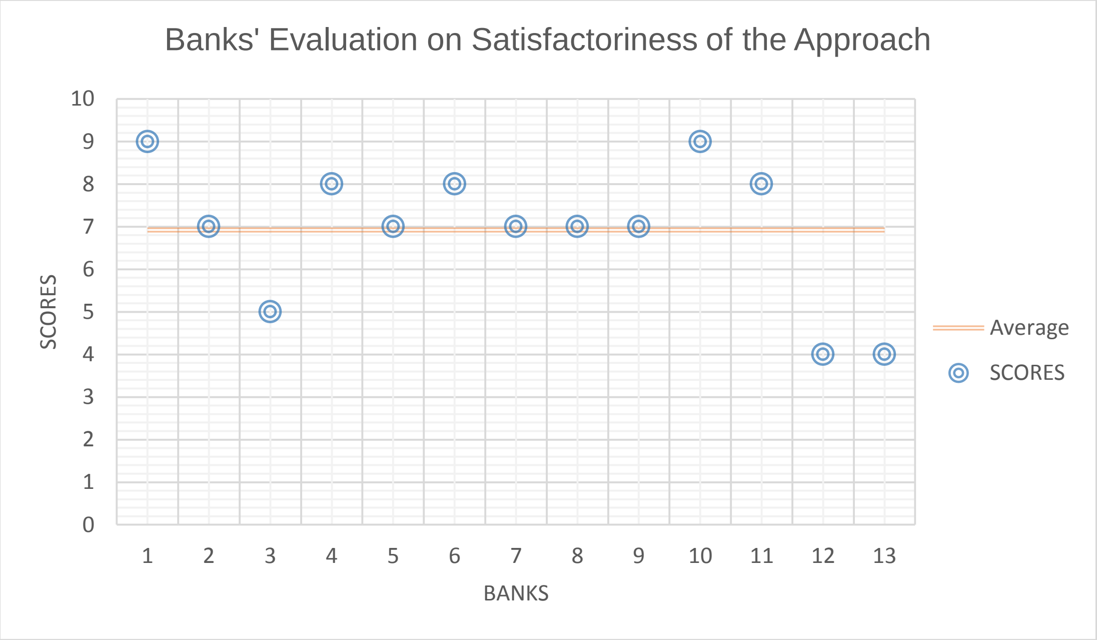


**Figure 32:** Evaluation of the banks on satisfactoriness of the approach proposed

The banks were invited to evaluate satisfactoriness of the approach proposed in overall. Significant number of banks put it at considerable sufficiency level while certain banks have stated that it does not sufficiently meet their expectations as indicated in Figure 32. The average satisfaction level is about 7 out of 10. Most scores are near or over the average value.

Banks were invited to comment on whether there is any deficiency to fulfill or areas to improve about the approach proposed. Opinions of the banks on the subject are outlined in Table 34. Eight banks have commented on the subject, four of which state that there is no deficiency in the approach and no need for further improvement. Five banks have no comment on the subject. Suggestions for improvement mostly have concern for focus on controls while maintaining the approach. Those controls include development of separate methodology and separate systems such as control on acceptance of data from other sources. One bank stresses the need for an adaptive infrastructure in order to handle the changes or shifts driven by the approach. Another bank has stated the need for another system for data archiving.

**Table 34** Banks' comment on deficiencies and possible improvement areas of the approach proposed

| Bank No | Deficiencies and possible suggestions for improvement |
|---|---|
| **Bank1** | The approach has great similarity with the data quality project for rating systems initiated by our (the bank's) risk management department. The extent of the assessment rules is key for maintaining the system soundly. Therefore, a different methodology for evaluation of those rules can be developed. |
| **Bank2** | (No comment) |
| **Bank3** | (No comment) |
| **Bank4** | Arranging operations regarding first time retrieval of the data is vital to accuracy of the data. Consistency of the data can be checked in order to ensure control retrieval of the data. |
| **Bank5** | No deficiency exists and no further improvement is required. |
| **Bank6** | (No comment) |
| **Bank7** | Another system for data archiving (especially for non-performing loans and collaterals) is suggested. |
| **Bank8** | No deficiency exists and no further improvement is required. |
| **Bank9** | No deficiency exists and no further improvement is required. |
| **Bank10** | No deficiency exists and no further improvement is required. |
| **Bank11** | An adaptive infrastructure should be built. |
| **Bank12** | (No comment) |
| **Bank13** | (No comment) |

Banks were also asked to state what type of difficulties they may face in practical application of the approach. Opinions submitted by the banks on the subject are summarized in Table 35. Four banks have no comment on the subject. One bank thinks that it can be applied through all banks with ease. Most of the concerns about the practical applicability of the approach concentrate on requirement for change in IT infrastructure of the bank, financial and qualified human resources, and on compatibility issues.

**Table 35** Banks' comment on potential difficulties in practical application of the approach

| Bank No | Potential difficulties in practical application of the approach |
|---|---|
| **Bank1** | Since change in data (due to changes in model, shifts in systems etc.) in daily operations is too fast, dedicated teams should be set up to manage the system and support of the senior management to those teams is very crucial. The support of the senior management has critical significance especially for adopting data stewardship in all data quality/data governance projects by business units. |
| **Bank2** | (No comment) |
| **Bank3** | No internal model is used within the bank, credit risk is calculated via simple method. Data required for calculation is obtained from core banking system. Quality of data used in core banking system is managed in accordance with the regulation relevant to information system management. |
| **Bank4** | Accordance with banking systems is critical |
| **Bank5** | There might be difficulties in integration of rating systems to local systems |
| **Bank6** | (No comment) |
| **Bank7** | There might be difficulties in allocating financial and human resources |
| **Bank8** | It is a project that requires to have expert staff in IT, and participation of the relevant departments. Therefore, there might arise resource issues and prioritization problems while working through the project. |
| **Bank9** | Since implementation of the approach requires significant studies and arrangements in system infrastructure, it rises the issue of requirements for significant time and workforce. |
| **Bank10** | The approach proposed seems to be applicable by all financial institutions. |
| **Bank11** | It may require evaluation in terms of its harmony with portfolio structure of the bank. |
| **Bank12** | (No comment) |
| **Bank13** | (No comment) |

## 5.3 Evaluation of the Survey Findings

The average experience of the managers from 13 banks who responded to survey questions is about 16 years. The banks which participated in the survey belong to different range in terms of their size and core business in the Turkish banking sector.

The attitude and activities regarding the DQA of credit risk within the banks are considerably in line with the content of DQA approach proposed. The approach is evaluated as extensively addressing data quality issues of the banks. Most banks are confident with what the approach presents and they are willing to implement it to certain extent. Evaluations of the banks on their own DQA activities and on the approach proposed are remarkably consistent with each other.

# CHAPTER 6

# DISCUSSION AND CONCLUSION

This chapter is devoted to discussion of the findings of the study, the conclusion of the study, contribution of the study to the literature of DQA in the context of credit risk management, and recommendations for future research in this field.

## 6.1 Discussion

The studies related to DQA in the context credit risk management in the literature usually focus on subjective assessment of DQ in credit risk management. Empirical studies using questionnaires conducted at the managerial levels in financial firms suggest methods for improvement of DQ based on statistical findings obtained from analyzing the results of the questionnaires (Moges et al., 2013). Some other studies propose the best practice solutions such as a centralized approach to risk data or integration of risk and finance data to improve DQ of risk data of financial institutions based on regulatory requirements of the Basel framework (Bonollo & Neri, 2011). Some studies present an approach that considers both quantitative and qualitative aspects (Yin et al., 2014). However, there is a clear need for objective assessment based on DQ metrics developed for the fundamental entities of credit risk. The present study explored the possibility of developing well-defined DQ metrics for credit risk management.

For this purpose, the study first attempted to designate categorization of credit risk data; that is, data taxonomy of the context in accordance with the Basel Accords is identified. The following main entities are identified as candidates for root data tables in credit risk management practices: obligors, transactions and credit protections. Attributes for each entity are also identified based on the characteristics of those entities. The reason for such taxonomy is the aim to reduce dependencies among the tables in the databases of banks and reduce DQ related problems proactively by modularizing data tables based on the characteristics of the entities. What distinguishes this study from the other studies dealing with DQA is its proactive structure in the definition phase of the approach. Proposal of appropriate and efficient decomposition of entities, more specifically root data tables, give the risk manager of banks the clue for initial elimination of the most DQ challenges. Relational tables can be grounded the root tables identified in the definition phase, which allows the banks to manipulate their data tables flexibly in order to produce final reporting tables.

Determination of proper data taxonomy is not sufficient for initial inspection of vulnerabilities to poor DQ risk. Investigation of original sources of the identified attributes of the entities is also crucial in detecting major causes of DQ issues. A complex IS infrastructure where various raw data required by risk management system are obtained from not-so-well disintegrated or highly dependent systems, i.e. low modular systems, may cause labyrinthical DQ problems resolution of which can be burdensome. The study proposes the use of the modular systems each of which specifically provides data for certain domain and supplements risk management system. Those systems supplement risk management system of the bank by providing data for specific domains of the tables, which are summarized in Table 36.

**Table 36** Risk management system and the supplementary systems proposed for risk management systems and possible domains that can be provided via those systems

| **Proposed supplementary system for risk management system** | **Possible domains that can be fed to risk management system** |
|---|---|
| Account Management System | Identity of the obligor (tax ID, client ID, account number, country and obligor type) financial statement of the obligor (turnover, active size and staff size) |
| Accounting System | Accounting record, transaction type, transaction amount (principal, return and provision), transaction period, transaction currency type |
| Rating System | Credibility of obligor, credibility of warrantor |
| Collateral Management System | Credit protection identity, protection type, protection period, protection currency type |
| Risk Management System | Risk group of the obligor, credit conversion factor |

DQ dimensions are defined according to DQ requirements of each attribute of an entity. The range of DQ dimensions are limited to those ones which are mostly cited in the literature. These are uniqueness, completeness, accuracy, consistency and timeliness. Those dimensions are selected since the approach proposed in the study mostly considers quantitative aspects of DQA, and their use in database applications is rather easy and common.

Other significant outcomes of the study are the definition and implementation of DQ metrics specifically designated for credit risk context, and quality performance indicators developed from those metrics. DQ metrics are developed for each attribute relevant for a given DQ dimensions. Specialization of DQ metrics for credit risk management purposes enables banks to develop systematic and standardized approach towards DQA of their databases, and allows comparative analysis of sector-wide credit risk data. Development of individual and composite quality performance indicators contributes to standardization and visualization of DQA results. Number of the proposed DQ metrics, KQPIs and CQPIs are tabulated in Table 37.

**Table 37** Number of DQ metrics, KQPIs, and CQPIs developed for each DQ dimension and entity

| DQ dimension | Entity name | Number of DQ metrics developed | Number of KQPIs developed | Number of CQPIs developed |
|---|---|---|---|---|
| Uniqueness | Obligors | 2 | 2 | 1 |
| | Transactions | 1 | 1 | |
| | Credit Protections | 1 | 1 | |
| | Credit Risk | 0 | 0 | |
| | **Total** | **4** | **4** | |
| Completeness | Obligors | 5 | 5 | 1 |
| | Transactions | 9 | 9 | |
| | Credit Protections | 7 | 7 | |
| | Credit Risk | 7 | 7 | |
| | **Total** | **28** | **28** | |
| Accuracy | Obligors | 3 | 3 | 1 |
| | Transactions | 4 | 4 | |
| | Credit Protections | 3 | 3 | |
| | Credit Risk | 1 | 1 | |
| | **Total** | **11** | **11** | |
| Consistency | Obligors | 3 | 3 | 1 |
| | Transactions | 2 | 2 | |
| | Credit Protections | 0 | 0 | |
| | Credit Risk | 7 | 7 | |
| | **Total** | **12** | **12** | |
| Timeliness | Obligors | 0 | 0 | 1 |
| | Transactions | 4 | 4 | |
| | Credit Protections | 2 | 2 | |
| | Credit Risk | 0 | 0 | |
| | **Total** | **6** | **6** | |
| ALL | **Grand Total** | **61** | **61** | **5** |

Evaluation of the DQ metrics proposed is performed by DQA methods such as column analysis, cross-domain analysis, domain analysis and semantic profiling. Although those methods are cited in the literature, there is no specific definition or procedure for such methods specifically for assessment of bank credit risk data since it depends on the data context. Therefore, SQL queries which can be regarded as special application of such methods are developed in order to measure the DQ metrics which will reveal DQ level of credit risk data.

Analysis and improvement phases of the proposed approach depend on the results of DQA. However, the study has provided guidance on possible DQ problems depending on the performance of CQPIs which are the composite indicators for DQ dimensions. DQ literature addresses handful DQ problems and their causes (Borek et al., 2011). Similarly, the present study has provided guidance for improvement areas and techniques depending on the size, complexity and criticality of causes of DQ problems revealed at analysis phase.

Implementation of these metrics for a real bank case has indicated weak aspects of the bank in terms of DQ via the results of KQPIs and CQPIs which were confirmed by the bank authorities.

The questionnaire prepared to assess validity, applicability and acceptance of the approach, and was completed by a number of banks from the Turkish banking sector gave an idea about the sufficiency and appropriateness of the approach evaluated by participant senior risk managers. Overall evaluation scores of the banks on the satisfactoriness of the approach along with self-evaluation of their own DQA activities are given in Figure 33.

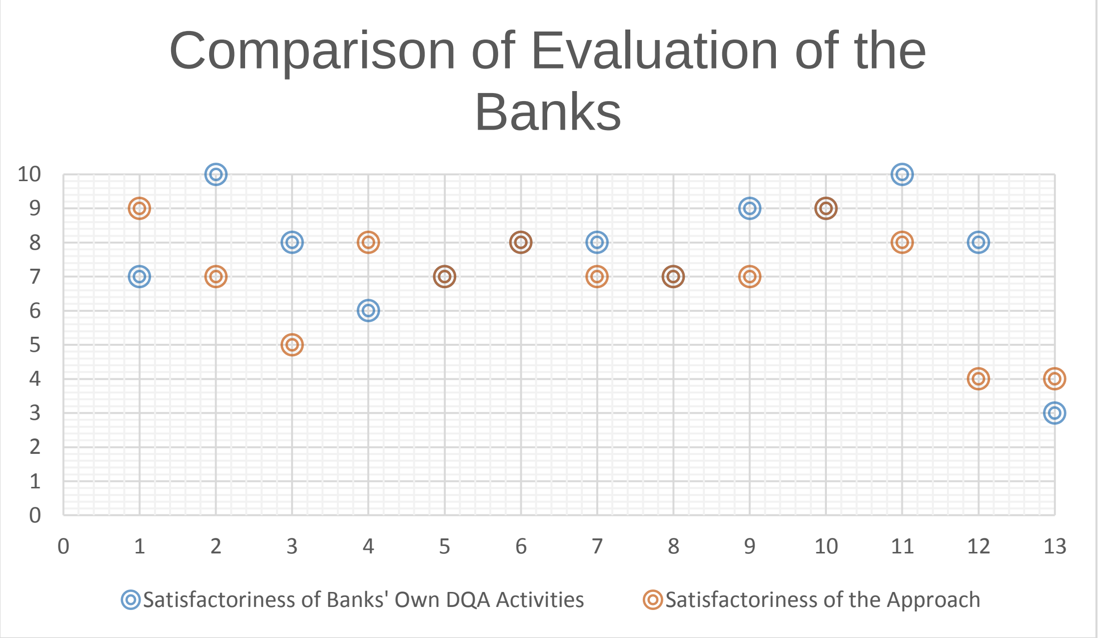


**Figure 33** Comparison of evaluation of the banks on the approach and their own DQA activities

## 6.2 Conclusion

This study has aimed to customize TDQM to credit risk management context in order to assess quality of credit risk data from IS viewpoint. Due to significance of banking data for maintenance of the financial system, DQA in this context plays important role in accurate quantification of their risks which enables banks to manage and control their credit risks.

The study started with reviewing the DQA literature. Then, the phases of TDQM were adopted in order to assess quality of credit risk data. The content of each phase was customized for credit risk context. In the proposed approach, data taxonomies for credit risk management and IT infrastructure are identified in the first phase. Development of DQ metrics and quality performance metrics contribute to DQA process. Measurement of those metrics via DQA methods, more specifically SQL queries, developed to assess DQ of credit risk produces DQA results. Those results reveal the DQ problems and enable investigation of underlying causes of those problems, which leads to the formulation of appropriate techniques for improvement of poor DQ.

Implementation of the study on credit risk data of a real bank has revealed the applicability and meaningfulness of the approach which is supported by the officers of the bank. In addition, a survey for evaluation of the approach carried out within numerous banks indicated validity and applicability of the approach.

It can be concluded that development of a tailored approach for DQA in credit risk management can provide indispensable benefits in achieving higher maturity level in IS capabilities. Those benefits range from identification of problematic areas that cause economic losses chronically to accurate quantification of credit risk which contribute to manage those risks and determine capital amount required to be hold.

## 6.3 Contribution of the Study

Studies dealing with DQA of credit risk focus on inquiring DQ challenges by interviewing with the managers from various financial institutions. Those studies usually rest on subjective assessment of DQ by the stakeholders of credit risk data production process (Moges et al., 2013). However, this study has mostly focused on quantitative aspects DQA and has developed DQ metrics specifically for the entities of credit risk. The study has contributed to the literature by proposing a tailored approach for DQA of credit risk management, customizing the phases of TDQM. TDQM proposed by Wang (1998) does not provide guidance on detailed implementation of the approach for a specific context but rather outlines fundamental structure of the phases. The present study elaborates on each phase of TDQM at a more granular level. Specifically, the definition and measurement phases constitute a significant part in the approach. Definition phase is not only restricted to definition of DQ dimensions but also includes identification of data taxonomies for credit risk. Measurement phase also provides detailed and specific definitions for DQ metrics, which is a significant contribution to that field.

## 6.4 Limitations of the Study and Future Research

Several limitations of the present study have to be pointed out.

Although the proposed TDQM customization for the purposes of this study in the context of credit risk management can be used for credit risk data under both SA and IRB approach, implementation of the definition phase of TDQM has been restricted to credit risk data under SA only. Number of data tables and fields can be different for the two approaches. Therefore, data quality requirements for SA and IRB approach may differ, thus, require definition of different DQ dimensions and DQ metrics. Moreover, IRB approach entails more sophisticated data requirements than those for SA, which necessitates definition of additional DQ dimensions. Implementation of the phases of TDQM for the data requirements of the IRB approach will have to be realized in future studies as the Turkish banking sector adopts and uses IRB approach in the near future.

Secondly, DQ dimensions investigated in this study only cover the mostly cited ones in the literature; namely, uniqueness, completeness, accuracy, consistency and timeliness. These dimensions overlap with a significant number of other DQ dimensions studied in the literature. Moreover, their suitability for direct use in objective assessments and database applications has motivated this study to select these DQ dimensions. However, the range of DQ dimensions can be extended to various other dimensions studied in the literature. For example, DQ dimensions proposed by Wang and Strong (1996) that are relevant to the credit risk management context can also be incorporated to the study.

Thirdly, implementation of the approach proposed has been performed only for just one bank. Possible extension of the implementation of such an approach to a wide range of banks in the sector will reveal the major DQ challenges in the sector. The extension of the application of the study to more banks will definitely contribute to the enhancement of DQ metrics developed, and thus to, DQA techniques.

Also, the fact that just 13 bank managers have responded to the evaluation survey discussed in Chapter 5 obviously indicates that further evaluations and possible adaptations to actual needs and requirements of the banking sector may be helpful in enhancing comprehensiveness as well as practicality of the proposed approach. As the number of responses was quite limited, we have intentionally refrained from attempting to derive any quantitative or universal interpretations of the evaluations provided. A more objective and wide ranging assessment of what we have proposed is definitely needed before any further work is undertaken in this direction.

In addition, the survey was conducted via emails sent to banks due to busy agenda of the senior managers. We do not know their background and familiarity with the IT issues and terminology although this issue has been addressed by providing explanatory information about the questions in addition to a condensed summary of the proposed approach. They were also invited to answer those questions with the assistance of senior IT staff. We know that some took this route.

Lastly, qualitative aspects of the DQA methods proposed can be strengthened via surveys pointing out inquiry and evaluation of IS infrastructure of the bank in terms of credit risk management, and DQ quality of databases utilized in credit risk management similar to those surveys carried out by Moges et al. (2013). Extension of the study in order to cover more subjective aspects will allow incorporation of further DQ dimensions into the approach.

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# APPENDICES

## APPENDIX A: DQ Dimensions Studied In the Literature

| DQ dimension | Definition/Description |
|---|---|
| Accuracy | Batini et al. (2009):<br>Syntactic accuracy: it is measured as the distance between the value stored in the database and the correct one<br>Syntactic Accuracy=Number of correct values/number of total values<br>Number of delivered accurate tuples<br>Moges et al. (2011 & 2013) and Moges (2014):<br>The extent to which data are certified, error-free, correct, flawless and reliable<br>Dejaeger et al. (2010):<br>Syntactic accuracy: It represents the approximation of a value to the elements of the corresponding domain D.<br>Semantic accuracy: It describes the approximation of a value x to the true value x'. |
| Completeness | Batini et al. (2009):<br>Completeness = Number of not null values/total number of values<br>Completeness = Number of tuples delivered/Expected number<br>Completeness of Web data = $(T_{max} – T_{current}) \ast (\text{Completeness}_{Max} – \text{Completeness}_{Current})/2$<br>Moges et al. (2011 & 2013) and Moges (2014):<br>The extent to which data are not missing and covers the needs of the tasks and is of sufficient breadth and depth of the task at hand<br>Dejaeger et al. (2010):<br>It is defined as to what extent there are no missing values (causal/not causal) |
| Consistency | Batini et al. (2009):<br>Consistency = Number of consistent values/number of total values<br>Number of tuples violating constraints, number of coding differences<br>Number of pages with style guide deviation<br>Dejaeger et al. (2010):<br>A data set can be said to be consistent when the constraints within each observation are met<br>Interrelational consistency: It deals with rules established for all the records within the data set<br>Intrarelational consistency: It verifies whether rules which are applicable within one record are being respected |
| Timeliness | Batini et al. (2009):<br>Timeliness = $(\max (0; 1\text{-Currency/Volatility}))^s$<br>Percentage of process executions able to be performed within the required time frame<br>Moges et al. (2011 & 2013) and Moges (2014):<br>The extent to which data are sufficiently up-to-date for the task at hand |

| | |
|---|---|
| | Dejaeger et al. (2010):<br>It represents how recent the data are in relation to their purpose. |
| Currency | Batini et al. (2009):<br>Currency = Time in which data are stored in the system - time in which data are updated in the real world<br>Time of last update<br>Currency = Request time- last update<br>Currency = Age + (Delivery time – Input time)<br>Dejaeger et al. (2010):<br>It concerns the immediate updating when a change occurs in the real-life counterpart x. |
| Volatility | Batini et al. (2009):<br>Time length for which data remain valid<br>Dejaeger et al. (2010):<br>It describes how frequent data change in time |
| Uniqueness | Batini et al. (2009):<br>Number of duplicates<br>Dejaeger et al. (2010):<br>Uniqueness viewed as a supplement to completeness by checking the presence of doubles in the data set |
| Appropriate amount of data | Batini et al. (2009):<br>Appropriate Amount of data = Min ((Number of data units provided/Number of data units needed); (Number of data units needed/Number of data units provided))<br>Moges et al. (2011 & 2013) and Moges (2014):<br>The extent to which the volume of information is appropriate for the task at hand |
| Accessibility | Batini et al. (2009):<br>Accessibility = max (0; 1-(Delivery time - Request time)/(Deadline time – Request time))<br>Number of broken links - Number of broken anchors<br>Moges et al. (2011 & 2013) and Moges (2014):<br>The extent to which data is available, or easily and swiftly retrievable |
| Credibility | Batini et al. (2009):<br>Number of tuples with default values |
| Interpretability | Batini et al. (2009):<br>Number of tuples with interpretable data, documentation for key values<br>Moges et al. (2011 & 2013) and Moges (2014):<br>The extent to which data are in appropriate languages,<br>symbols, and the definitions are clear |
| Derivation integrity | Batini et al. (2009):<br>Percentage of correct calculations of derived data according to the derivation formula or calculation definition |
| Conciseness | Batini et al. (2009):<br>Number of deep (highly hierarchic) pages |
| Maintainability | Batini et al. (2009):<br>Number of pages with missing meta-information |
| Applicability | Batini et al. (2009):<br>Number of orphaned pages |
| Convenience | Batini et al. (2009):<br>Difficult navigation paths: number of lost/interrupted navigation trails |
| Speed | Batini et al. (2009):<br>Server and network response time |
| Comprehensiveness | Dejaeger et al. (2010):<br>It refers to whether the end-user can fully understand the data |
| Traceability | Batini et al. (2009):<br>Number of pages without author or source |

| | |
|---|---|
| | Moges et al. (2011 & 2013) and Moges (2014):<br>The extent to which data is traceable to the source |
| Security | Batini et al. (2009):<br>Number of weak log-ins<br>Moges et al. (2011 & 2013) and Moges (2014):<br>The extent to which access to data is restricted appropriately to maintain its security<br>Dejaeger et al. (2010):<br>It is related to privacy and safety regulations<br>(IT-elements / human aspects) |
| Objectivity | Moges et al. (2011 & 2013) and Moges (2014):<br>The extent to which data are unbiased, unprejudiced, based on facts and impartial |
| Relevancy | Moges et al. (2011 & 2013) and Moges (2014):<br>The extent to which data are applicable and helpful for the task at hand |
| Reputation | Moges et al. (2011 & 2013) and Moges (2014):<br>The extent to which data are highly regarded in terms of its sources or content |
| Interactivity | Batini et al. (2009):<br>Number of forms - Number of personalizable pages |
| Value-added | Moges et al. (2011 & 2013) and Moges (2014):<br>The extent to which data are beneficial and provides advantages from its use |
| Actionable | Moges et al. (2011 & 2013) and Moges (2014):<br>The extent to which data is ready for use |
| Easily-understandable | The extent to which data are easily comprehended |
| Representational-consistency | Moges et al. (2011 & 2013) and Moges (2014):<br>The extent to which data are continuously presented in same format |
| Concisely-presented | Moges et al. (2011 & 2013) and Moges (2014):<br>The extent to which data is compactly represented, well-presented, well-organized, and well-formatted |
| Alignment | Moges et al. (2011 & 2013) and Moges (2014):<br>The extent to which data is reconcilable (compatible) |

# APPENDIX B: SQL Query Examples for DQ Dimensions

SQL queries for uniqueness

**Query1.** "SELECT Client_ID, COUNT(Client_ID) FROM CLIENTS GROUP BY Client_ID HAVING COUNT(Client_ID) > 1"

**Query2.** "SELECT Tax_ID, COUNT(Tax_ID) FROM CLIENTS GROUP BY Tax_ID HAVING COUNT(Tax_ID) > 1"

SQL queries for completeness

**Query3.** "SELECT COUNT(*) FROM CLIENTS WHERE Client_ID Is Null"

**Query4.** "SELECT COUNT(*) FROM CLIENTS WHERE Tax_ID Is Null"

**Query5.** "SELECT COUNT(*) FROM CLIENTS WHERE Client_Name Is Null"

**Query6.** "SELECT COUNT(*) FROM CLIENTS WHERE Risk_Category_Code Is Null"

**Query7.** "SELECT COUNT(*) FROM CLIENTS WHERE Risk_Category_Name Is Null"

**Query8.** "SELECT COUNT(*) FROM CLIENTS WHERE Country_Code Is Null"

**Query9.** "SELECT COUNT(*) FROM CLIENTS WHERE Client_Risk_Class Is Null"

**Query10.** "SELECT COUNT(*) FROM CREDITS WHERE Client_ID Is Null"

**Query11.** "SELECT COUNT(*) FROM CREDITS WHERE Tax_ID Is Null"

**Query12.** "SELECT COUNT(*) FROM CREDITS WHERE Credit_Account_No Is Null"

**Query13.** "SELECT COUNT(*) FROM CREDITS WHERE Trial_Balance_Code Is Null"

**Query14.** "SELECT COUNT(*) FROM CREDITS WHERE Credit_Type Is Null"

**Query15.** "SELECT COUNT(*) FROM CREDITS WHERE Credit_Open_Date Is Null"

**Query16.** "SELECT COUNT(*) FROM CREDITS WHERE Credit_Period Is Null"

**Query17.** "SELECT COUNT(*) FROM CREDITS WHERE Credit_Conversion_Factor Is Null"

**Query18.** "SELECT COUNT(*) FROM CREDITS WHERE Credit_Risk_Class Is Null"

**Query19.** "SELECT COUNT(*) FROM CREDITS WHERE Currency_Code Is Null"

**Query20.** "SELECT COUNT(*) FROM CREDITS WHERE Credit_Principal Is Null"

**Query21.** "SELECT COUNT(*) FROM CREDITS WHERE Credit_Risk_Weight Is Null"

**Query22.** "SELECT COUNT(*) FROM CREDITS WHERE Exposure_Before_CRM Is Null"

**Query23.** "SELECT COUNT(*) FROM CREDITS WHERE RWA_After_CRM Is Null"

**Query24.** "SELECT COUNT(*) FROM CREDITS WHERE Balance_Sheet_Class Is Null"

**Query25.** "SELECT COUNT(*) FROM CREDITS WHERE TB_or_BB Is Null"

**Query26.** "SELECT COUNT(*) FROM COLLATERALS WHERE Client_ID Is Null"

**Query27.** "SELECT COUNT(*) FROM COLLATERALS WHERE Client_Tax_ID Is Null"

**Query28.** "SELECT COUNT(*) FROM COLLATERALS WHERE Trial_Balance_Code Is Null"

**Query29.** "SELECT COUNT(*) FROM COLLATERALS WHERE Warrantor_Tax_ID Is Null"

**Query30.** "SELECT COUNT(*) FROM COLLATERALS WHERE Collateral_ID Is Null"

**Query31.** "SELECT COUNT(*) FROM COLLATERALS WHERE Collateral_Type Is Null"

**Query32.** "SELECT COUNT(*) FROM COLLATERALS WHERE Currency_Code Is Null"

**Query33.** "SELECT COUNT(*) FROM COLLATERALS WHERE Warrantor_Risk_Class Is Null"

**Query34.** "SELECT COUNT(*) FROM COLLATERALS WHERE Collateral_Fair_Value Is Null"

**Query35.** "SELECT COUNT(*) FROM COLLATERALS WHERE Collateral_Value_Allocated Is Null"

**Query36.** "SELECT COUNT(*) FROM COLLATERALS WHERE Collateral_Country_Code Is Null"

**Query37.** "SELECT COUNT(*) FROM COLLATERALS WHERE Collateral_Period Is Null"

SQL queries for accuracy

**Query38.** "SELECT COUNT(*) FROM CLIENTS WHERE Client_Risk_Class NOT LIKE 'MRS[1-9]' AND Client_Risk_Class NOT LIKE 'MRS1[0-3]' "

**Query39.** "SELECT COUNT(*) FROM CLIENTS WHERE Firm_Segment <> 'KI' AND Firm_Segment <> 'KOBI' AND Firm_Segment IS NOT NULL"

**Query40.** "SELECT COUNT(*) FROM CREDITS WHERE Trial_Balance_Code LIKE '%[!0-9]%'"

**Query41.** "SELECT COUNT(*) FROM CREDITS WHERE Credit_Type <> 'NK' AND Credit_Type <> 'NKKF' AND Credit_Type NOT LIKE 'GNA0[1-9]' AND Credit_Type NOT LIKE 'GNA1[0-3]' AND Credit_Type NOT LIKE 'GNB0[1-6]' AND Credit_Type NOT LIKE 'GN[CD]0[1-7]' AND Credit_Type NOT LIKE 'KTR0[1256789]' AND Credit_Type NOT LIKE 'KTR0[56][AB]' AND Credit_Type NOT LIKE 'KTR10' AND Credit_Type NOT LIKE 'DA'";

**Query42.** "SELECT COUNT(*) FROM CREDITS WHERE Credit_Conversion_Factor <> 0 AND Credit_Conversion_Factor <> 0.2 AND Credit_Conversion_Factor <> 0.5 AND Credit_Conversion_Factor <> 1"

**Query43.** "SELECT COUNT(*) FROM CREDITS WHERE Credit_Risk_Class NOT LIKE 'ARS0[1-9]' AND Credit_Risk_Class NOT LIKE 'ARS1[0-9]' AND Credit_Risk_Class NOT LIKE 'ASH99'"

**Query44.** "SELECT COUNT(*) FROM CREDITS WHERE Credit_Quality_Level <> 1 AND Credit_Quality_Level <> 2 AND Credit_Quality_Level <> 3 AND Credit_Quality_Level <> 4 AND Credit_Quality_Level <> 5 AND Credit_Quality_Level <> 6"

**Query45.** "SELECT COUNT(*) FROM CREDITS WHERE Credit_Risk_Weight <> 0 AND Credit_Risk_Weight <> 0.2 AND Credit_Risk_Weight <> 0.5 AND Credit_Risk_Weight <> 0.75 AND Credit_Risk_Weight <> 1 AND Credit_Risk_Weight <> 1.5 AND Credit_Risk_Weight <> 2 AND Credit_Risk_Weight <> 2.5 "

**Query46.** "SELECT COUNT(*) FROM CREDITS WHERE Balance_Sheet_Class < 1 OR (Balance_Sheet_Class > 20 AND Balance_Sheet_Class <> 27 AND Balance_Sheet_Class <> 48 AND Balance_Sheet_Class <> 50 AND Balance_Sheet_Class <> 51) "

**Query47.** "SELECT COUNT(*) FROM CREDITS WHERE TB_or_BB <> 'TB' AND TB_or_BB <> 'BB'"

**Query48.** "SELECT COUNT(*) FROM CREDITS WHERE Foreign_Exchange_Indexed <> 'Y' AND Foreign_Exchange_Indexed IS NOT NULL"

**Query49.** "SELECT COUNT(*) FROM COLLATERALS WHERE Collateral_Type NOT LIKE 'T[1-9]' AND Collateral_Type NOT LIKE 'T1[0-2]'"

**Query50.** "SELECT COUNT(*) FROM COLLATERALS WHERE Warrantor_Risk_Class NOT LIKE 'TRS0[1-9]' AND Warrantor_Risk_Class NOT LIKE 'TRS1[0-6]'"

**Query51.** "SELECT COUNT(*) FROM COLLATERALS WHERE Collateral_Risk_Weight <> 0 AND Collateral_Risk_Weight <> 0.2 AND Collateral_Risk_Weight <> 0.5 AND Collateral_Risk_Weight <> 0.75 AND Collateral_Risk_Weight <> 1 AND Collateral_Risk_Weight <> 1.5 AND Collateral_Risk_Weight <> 2 AND Collateral_Risk_Weight <> 2.5 "

**Query52.** "SELECT COUNT(*) FROM COLLATERALS WHERE Mortgage_Degree NOT LIKE '[1-3]' AND Mortgage_Degree IS NOT NULL "

SQL queries for consistency

**Query53.** "SELECT Client_ID, COUNT(Tax_ID) FROM CLIENTS GROUP BY Client_ID HAVING COUNT(Tax_ID) > 1"

**Query54.** "SELECT Tax_ID, COUNT(Client_ID) FROM CLIENTS GROUP BY Tax_ID HAVING COUNT(Client_ID) > 1"

**Query55.** "SELECT Risk_Category_Code, COUNT(Risk_Category_Name) FROM CLIENTS GROUP BY Risk_Category_Code HAVING COUNT(Risk_Category_Name) > 1"

**Query56.** "SELECT Risk_Category_Name, COUNT(Risk_Category_Code) FROM CLIENTS GROUP BY Risk_Category_Name HAVING COUNT(Risk_Category_Code) > 1"

**Query57.** "SELECT COUNT(*) FROM CLIENTS WHERE ((Client_Risk_Class = 'MRS8' OR Client_Risk_Class = 'MRS9') AND Firm_Segment <> 'KOBI') OR ((Client_Risk_Class <> 'MRS8' AND Client_Risk_Class <> 'MRS9') AND Firm_Segment = 'KOBI') OR (Client_Risk_Class = 'MRS7' AND Firm_Segment <> 'KI') OR (Client_Risk_Class <> 'MRS7' AND Firm_Segment = 'KI') "

**Query58.** "SELECT COUNT(*) FROM CLIENTS WHERE ((Firm_Turnover = 0 OR Firm_Turnover IS NULL) AND (Firm_Segment = 'KOBI' OR Firm_Segment = 'KI')) OR (Firm_Turnover > 0 AND (Firm_Segment <> 'KOBI' OR Firm_Segment <> 'KI'))"

**Query59.** "SELECT COUNT(*) FROM CLIENTS WHERE ((Firm_Personnel_Number = 0 OR Firm_Personnel_Number IS NULL) AND (Firm_Segment = 'KOBI' OR Firm_Segment = 'KI')) OR (Firm_Personnel_Number > 0 AND (Firm_Segment <> 'KOBI' OR Firm_Segment <> 'KI')) "

**Query60.** "SELECT COUNT(*) FROM CLIENTS WHERE ((Firm_Asset_Size = 0 OR Firm_Asset_Size IS NULL) AND (Firm_Segment = 'KOBI' OR Firm_Segment = 'KI')) OR (Firm_Asset_Size > 0 AND (Firm_Segment <> 'KOBI' OR Firm_Segment <> 'KI'))"

**Query61.** "SELECT COUNT(*) FROM CREDITS WHERE ((Credit_Type = 'NK' OR Credit_Type = 'NKKF' OR Credit_Type = 'DA' OR Credit_Type LIKE 'KTR0[1256789]' OR Credit_Type LIKE 'KTR0[56][AB]' OR Credit_Type LIKE 'KTR10' OR Credit_Type LIKE 'GNA0[1-9]' OR Credit_Type LIKE 'GNA1[0-3]') AND Credit_Conversion_Factor <> 1) OR (Credit_Type LIKE 'GNB0[1-6]' AND Credit_Conversion_Factor <> 0.5) OR (Credit_Type LIKE 'GNC0[1-7]' AND Credit_Conversion_Factor <> 0.2) OR (Credit_Type LIKE 'GND0[1-7]' AND Credit_Conversion_Factor <> 0)"

**Query62.** "SELECT COUNT(*) FROM COLLATERALS WHERE (Collateral_Type = 'T6' AND Mortgage_Value Is Null) OR (Collateral_Type <> 'T6' AND Mortgage_Value Is Not Null)"

**Query63.** "SELECT COUNT(*) FROM COLLATERALS WHERE (Collateral_Type = 'T6' AND Mortgage_Degree Is Null) OR (Collateral_Type <> 'T6' AND Mortgage_Degree Is Not Null)"

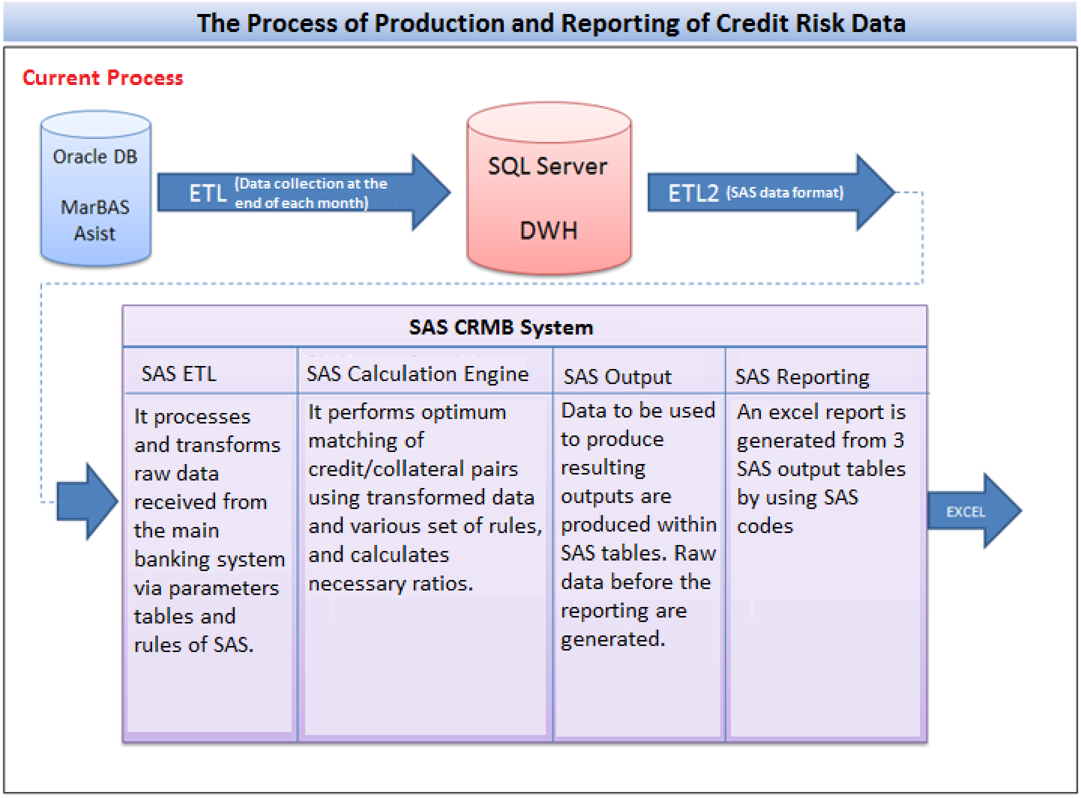
**Query64.** "SELECT COUNT(*) FROM COLLATERALS WHERE (Collateral_Type = 'T6' AND Mortgage_No Is Null) OR (Collateral_Type <> 'T6' AND Mortgage_No Is Not Null)"

**Query65.** "SELECT COUNT(*) FROM COLLATERALS WHERE (Collateral_Type = 'T6' AND Appraisal_Firm_Name Is Null) OR (Collateral_Type <> 'T6' AND Appraisal_Firm_Name Is Not Null)"

**Query66.** "SELECT COUNT(*) FROM COLLATERALS WHERE (Collateral_Type = 'T6' AND Appraisal_Report_Code Is Null) OR (Collateral_Type <> 'T6' AND Appraisal_Report_Code Is Not Null)"

**Query67.** "SELECT COUNT(*) FROM COLLATERALS WHERE (Collateral_Type = 'T6' AND Last_Appraisal_Date Is Null) OR (Collateral_Type <> 'T6' AND Last_Appraisal_Date Is Not Null)"

# APPENDIX C: Current Process for Credit Risk Data Production and Reporting in ABC Bank



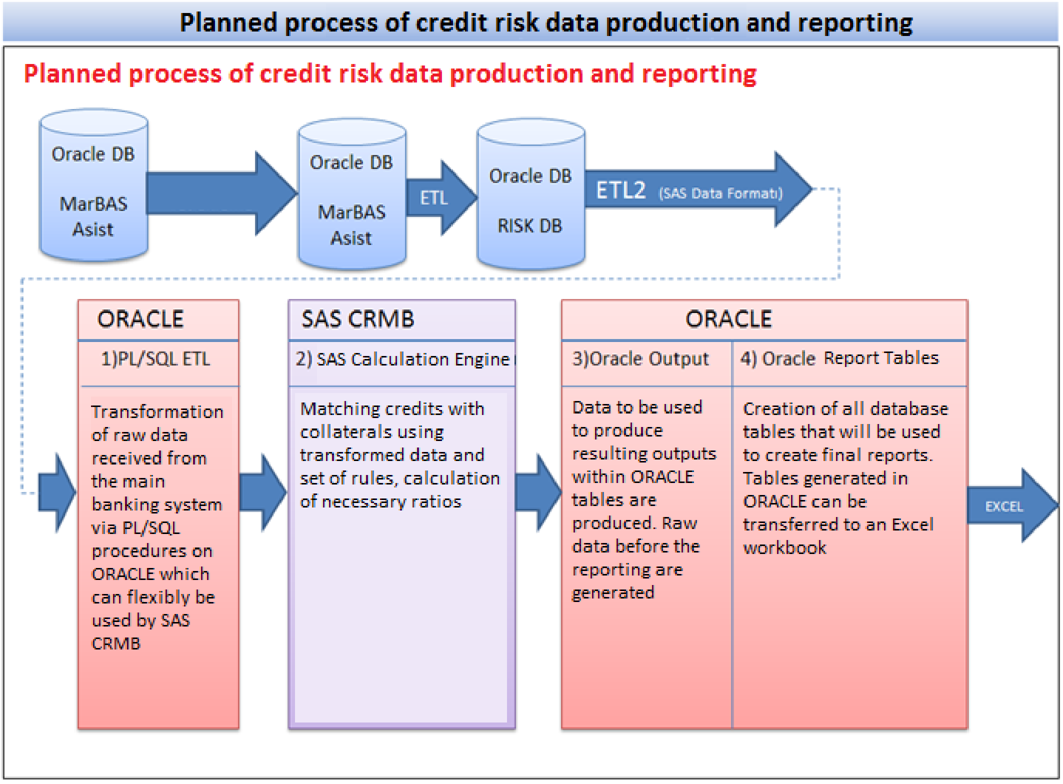
The Process of Production and Reporting of Credit Risk Data

Current Process

SAS CRMB System

| SAS ETL | SAS Calculation Engine | SAS Output | SAS Reporting |
|---|---|---|---|
| It processes and transforms raw data received from the main banking system via parameters tables and rules of SAS. | It performs optimum matching of credit/collateral pairs using transformed data and various set of rules, and calculates necessary ratios. | Data to be used to produce resulting outputs are produced within SAS tables. Raw data before the reporting are generated. | An excel report is generated from 3 SAS output tables by using SAS codes |

# APPENDIX D: Planned Process for Credit Risk Data Production and Reporting in ABC Bank



Planned process of credit risk data production and reporting

Planned process of credit risk data production and reporting

ORACLE

1)PL/SQL ETL

Transformation of raw data received from the main banking system via PL/SQL procedures on ORACLE which can flexibly be used by SAS CRMB

SAS CRMB

2) SAS Calculation Engine

Matching credits with collaterals using transformed data and set of rules, calculation of necessary ratios

ORACLE

3)Oracle Output

Data to be used to produce resulting outputs within ORACLE tables are produced. Raw data before the reporting are generated

4) Oracle Report Tables

Creation of all database tables that will be used to create final reports. Tables generated in ORACLE can be transferred to an Excel workbook

# APPENDIX E: Questionnaire for Data Quality Assessment of Banks' Credit Risk

Title of the participant[4]: ……………………………………………………………….

Department of the participant: ……………………………………………………...

Experience of the participant in banking sector (years): ……………………………...

This questionnaire is formed as a part of a Master of Science thesis study carried out in *Department of Information Systems, Graduate School of Informatics of the Middle East Technical University*. The questionnaire aims to evaluate an approach proposed to assess quality of data used to quantify, measure and calculate credit risk of banks based on responses obtained from the banks, and to improve the approach based on the results of the evaluation. The first part of the questionnaire (Part A) involves questions related to ongoing activities on data quality assessment within the banks, and the second part (Part B) involves questions related to banks' evaluation of the approach proposed by the study. A brief summary of the approach has been provided in Appendix-1 of the questionnaire.

The questionnaire has 36 questions in total, which roughly takes 15 to 20 minutes to complete.

Important Note: *Responses given to questionnaire will not be used for any other purposes but only for academic research. Privacy of identities of the participants will be ensured and they will not be shared with third parties.*

[4] The questionnaire is expected to be answered by senior managers of risk management departments of the banks. While filling out the questionnaire, it is advised to take assistance from senior IT personnel who are functional in providing IT infrastructure and database applications.

## A. DATA QUALITY ASSESSMENT ACTIVITIES WITHIN THE BANK

1- Do you think that a specific approach or method is required to assess quality of credit risk data of banks?

  a. Definitely not required
  b. Partially required
  c. Considerably required
  d. Definitely required

2- Are there any ongoing activities for quality assessment of credit risk data of your bank?

  a. Yes
  b. No

3- Which one(s) of following activities are involved in quality assessment of credit risk data of your bank? (multiple choice is possible)

  a. Data taxonomy of credit risk data
  b. Detection of credit risk data sources and integration of them to risk management system
  c. Definition of data quality dimensions for risk data
  d. Development of data quality metrics to measure quality of risk data
  e. Measurement of data quality performance via data quality metrics
  f. Analysis quality performance and detection of causes of poor data quality
  g. Identification of improvement areas and actions to solve data quality issues
  h. Doing comprehensive cost/benefit analysis for viable improvement actions
  i. Other (state)………………………………………………………………
  j. None

4- Is quality assessment of credit risk data of your bank based on qualitative or quantitative assessment? (1-purely qualitative, 10- purely quantitative assessment)

Qualitative ← ① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩ → Quantitative

5- Under which categories (data table type and number) does your bank classify final data used in calculation of credit risk? (e.g. clients, credits, collaterals etc.)

………………………………………………………………………………………

…………………………………………………………………..

6- Which systems or databases does risk management department require to provide raw data before creating final data for credit risk? (multiple choice is possible)

   a. Client Account Management System (client personal information and account information)
   b. Accounting System (accounting records regarding client transactions)
   c. Collateral Management System (collaterals and guarantees of clients)
   d. Rating System (ratings belonging to clients and collaterals)
   e. Other (state)…………………………………………………………
   f. None

7- While assessing data quality, it might require to use more than one data quality dimension depending on requirements and their relevance. ***Completeness*** is described as requirement for a data field not to have null values; ***uniqueness*** is described as requirement for a data field not to have duplicate values; ***consistency*** is described as requirement for conformance of data values in a data field to data values in another data field due to business rules and their relations to each other; ***accuracy*** is described as requirement for conformance of data values in a data field due to rules or constraints defined for that field; and ***timeliness*** is described as requirement for data values in a data field to be up-to-date based on a reference time point. Which data quality dimensions does your bank use in quality assessment of credit risk data? (multiple choice is possible)

   a. Completeness
   b. Uniqueness
   c. Consistency
   d. Accuracy
   e. Timeliness
   f. Other (state)…………………………………………………………
   g. None

8- Does your bank use quality performance metrics related to data quality dimensions in order to measure data quality?

   a. Yes, it does
   b. No, it does not

9- Various control techniques can be used in the data quality assessment processes and database applications. Examples for such techniques are provided in the following table.

| **DQA Method** | **Description** |
|---|---|
| Column analysis | Computation related to uniqueness, null values, min and max value, totals, standard deviations, inferred types etc. in a column |
| Cross-domain analysis | Identification of redundant data across columns in the same or different tables |
| Data validation | Verification of values against a reference data set via algorithms |
| Domain Analysis | Checking if a data value within certain domain of values |
| Lexical Analysis | Mapping unstructured content to structured set of attributes |
| Matching Algorithms | Identification of duplicate values |
| Primary Key / Foreign Key Analysis | Analysis applied to columns from different tables to detect good candidates for Primary Key /Foreign Key relation |
| Schema Matching | Detection of semantically equivalent attributes via algorithms |
| Semantic Profiling | Business rules on data in columns or tables and measurement of the compliance of data to the rules |

Which data quality assessment techniques does your bank use to measure quality of data in the database of the bank? (Multiple choice is possible)

a. Column analysis
b. Data validation
c. Cross-domain analysis
d. Domain analysis
e. Primary key / foreign key analysis
f. Semantic profiling
g. Lexical analysis
h. Matching algorithms
i. Schema matching
j. Other (state)…………………………………………………………

10- Does any prioritization take place for data types used in credit risk management of which you think that quality concern and sensitivity is critical?

a. Yes, it does.
b. No, there is no prioritization (same quality sensitivity is attributed to all data types).

11- Which goals or concerns are overseen while assessing data quality in credit risk management? (Rank those goals according to their significance starting from “1”)

a. Allocating accurate capital by accurate calculation of credit risk (   )
b. Verifying quality of data obtained via information system of the bank, and used in credit risk management (   )
c. Enhancing reliability of data used as input for credit risk management (   )
d. Other (state)…………………………………………………………

e. There is no concern for data quality of credit risk data of the bank.

12- Which problems does your bank experience about quality of credit risk data? (Multiple choice is possible)

a. Duplicate records
b. Missing data values
c. Data values violating domain constraints
d. Inconsistency of data values in different fields or tables
e. Outdated data values
f. Other (state)……………………………………………………………
g. None

13- What are the causes of data quality issues experienced in credit risk by your bank? (Rank those causes according to their significance starting from “1”)

a. Manual data entry (   )
b. Problems faced during consolidation of data obtained by multiple tables (   )
c. Inadequacy of IT infrastructure (e.g. odd and non-communicating tables) (   )
d. Complexity of IT infrastructure (   )
e. Use of many temporary tables during the creation of final tables (   )
f. Lack of central database (   )
g. Inability to update data simultaneously in all other tables when an update of data is made in a table (   )
h. Lack of controls for data constraints (   )
i. Inaccurate definition of business rules (   )
j. Other (state)……………………………………………………………
k. None

14- Which improvement methods have already been applied in your bank to solve data quality issues?

a. Patch solutions that do not seriously change IT infrastructure (changes not affecting major processes but minor steps)
b. Solutions that partly change IT infrastructure (partial changes in major processes)
c. Solutions/investments that significantly change IT infrastructure (significant changes in major processes)
d. No activity regarding selection of viable improvement methods has been performed before within the bank

15- Which criteria does your bank take into consideration while selecting methods for improvement of data quality? (Rank selected criteria according to their significance starting from “1”)

a. Costs of the method (including cost of investment, application and management) (   )
b. Benefits of the method (including contribution to reduction of operational costs) (   )
c. Practical applicability of the method (including burden of application and influence on relevant systems) (   )
d. Acceptance of the method within the bank (   )
e. Legal applicability of the method (   )
f. Other (state)……………………………………………………………
g. No activity regarding selection of viable improvement methods has been performed before within the bank

16- If there are activities regarding quality assessment of credit risk data within your bank, evaluate its satisfactoriness between the scores 1 and 10 (1- Completely unsatisfactory, 10- Completely satisfactory).

① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩

## B. EVALUATION OF BANKS ON THE APPROACH PROPOSED

17- Data taxonomy for credit risk data has been created in definition phase of the approach. Data are classified under three entities, i.e. obligors, transactions and credit protections, based on their characteristics. Attributes for entity has been identified. Additionally, forth entity (credit risk function) with its attributes is derived from other three entities (See Appendix, Definition phase). Do you find the data taxonomy created sufficient in terms of quality management of credit risk data?

a. Quite insufficient
b. Insufficient
c. Sufficient
d. Quite sufficient

18- Evaluate the following attributes belonging to obligors entity according to significance for credit risk management. (1-very important, 5-not important at all)

a. Obligor Identity (ID) (   )
b. Obligor Type (Class) (   )
c. Financial Statement of Obligor (for firms; revenue and asset size) (   )
d. Staff Size (for firms) (   )
e. Obligor Credibility (rating) (   )
f. Risk Group (   )

19- Evaluate the following attributes belonging to transactions entity according to significance for credit risk management. (1-very important, 5-not important at all)

a. Transaction Identity (ID) (   )
b. Accounting Record (   )
c. Transaction Type (   )
d. Credit Conversion Factor (   )
e. Transaction Amount (   )
f. Transaction Return (   )
g. Provisions/Losses (   )
h. Transaction Maturity (   )
i. Transaction Currency (   )

20- Evaluate the following attributes belonging to credit protections entity according to significance for credit risk management. (1-very important, 5-not important at all)

a. Credit Protection Identity (ID) (   )
b. Protection Type (   )
c. Protection Amount (   )
d. Protection Maturity (   )
e. Protection Rating (   )
f. Protection Currency (   )

21- Evaluate the following attributes belonging to credit risk function entity according to significance for credit risk management. (1-very important, 5-not important at all)

a. Obligor Identity (ID) (   )
b. Transaction Identity (ID) (   )
c. Protection Identity (ID) (   )
d. Final Rating (after matching obligor with credit protection) (   )
e. Exposure Before Credit Risk Mitigation (   )
f. Allocated Credit Protection Amount (   )
g. Risk Weighted Exposure After Credit Risk Mitigation (   )

22- Data sources that data related to attributes of entities proposed by the approach can be obtained are classified by the approach under certain systems (See part A) as follows. To what extent do you think those systems are appropriate (comprehensive and modular) in terms of credit risk management? (1-very appropriate, 5- not appropriate at all)
   a. Client Account Management System – contains personal information and account information of obligors (   )
   b. Accounting System – contains accounting records belonging to transactions of obligors (   )
   c. Collateral Management System – contains information about collaterals and guarantees of obligors (   )
   d. Rating System – contains ratings belonging to obligors and collaterals (   )
   e. Risk Management System – contains (derived) information other than those obtained from other systems  (   )

23- What do you think about satisfactoriness of data source system provided by the approach in the definition phase?
   a. Yes, satisfactory
   b. No, it is unsatisfactory; data sources that can be added (state)…………………………

24- Evaluate following data quality dimensions that are used in the proposed data quality assessment approach in terms of their relevance to credit risk? (1-completely relevant, 5-not relevant at all)
   a. Completeness (  )
   b. Uniqueness (  )
   c. Consistency (  )
   d. Accuracy (  )
   e. Timeliness (  )

25- Data quality dimensions proposed by the approach to assess credit risk data quality are uniqueness, completeness, consistency, accuracy and timeliness (Definitions have been provided in question 7). What do you think satisfactoriness of those dimensions in terms of their comprehensiveness?
   a. Yes, satisfactory
   b. No, it is unsatisfactory; data dimensions that can be added (state)……………………

26- In the measurement phase of the approach, to what extent do you think developing metrics by the approach to measure performance of data quality dimensions for each attribute of the entities contribute to credit risk management and data quality management?

  a. No contribution made
  b. No significant contribution made
  c. Partial contribution made
  d. Significant contribution made

27- In the measurement phase, assessment techniques that the approach focuses on are primary key/foreign key analysis, column analysis, cross-domain analysis, domain analysis and semantic profiling. SQL queries created based on those techniques are used to measure the metrics created in this phase. What do you think about effectiveness of those techniques used and queries created by the approach in measurement of quality of credit risk data?

  a. No effect at all
  b. No significant effect
  c. Partial effect
  d. Significant effect

28- In the measurement phase, key (individual) quality performance indicators for each metric are developed to assess results of performance metrics more meaningfully based on scores. Those indicators transforms metric results to scores based on a scale (e.g. out of 10). Individual indicators for each relevant data quality dimension are aggregated with certain weights in order to calculate composite quality performance indicators for each relevant data quality dimension. Do you think that deriving and calculating composite indicators from individual indicators will accurately represent and measure performance of relevant data quality dimension?

  a. Yes, I do
  b. No, individual indicators would be better indicator or different kind of metrics could be developed

29- If you think that composite indicators are significant and effective, how do you think that weights of individual indicators that composite ones is derived should be determined?

  a. Equal weights should be given.
  b. They should be prioritized according to their significance for credit risk calculation.
  c. They should be prioritized according to the complexity extent of transformation they are exposed while obtaining final data.
  d. The weights can be changed depending on changes in credit risk management functions.

30- In case that approach is implemented within your bank, which data quality issues do you think it will detect and provide support to find solutions to those issues in the analysis phase?

a. Duplicate records
b. Missing data values
c. Data values violating domain constraints
d. Inconsistency of data values in different fields or tables
e. Outdated data values
f. Other (state)………………………………………………………………
g. None

31- If your bank were to use the approach proposed, what should be the basis point in selecting improvement techniques in terms of their benefits and costs in order to solve data quality problems in the improvement phase?

a. They should be selected based on their benefits regardless of their costs.
b. The costs are critical for the bank; therefore, the selection criteria should mostly be based on the costs.
c. Both benefits and costs should be regarded as equally important in selecting the techniques.

32- Would you like to use the approach proposed at your bank? If you would, what is the reason such use?

a. Yes, data quality problems in our bank are at serious level.
b. Yes, partial implementation of the approach could be beneficial for our bank.
c. No, since we do not experience data quality problems, there is no such need.
d. No, we experience data quality problems but such an approach would be insufficient in resolving those problems.

33- Let us say you have used the approach proposed in your bank. Thus, you have obtained certain results based performance of metrics with that approach. To what extent would you trust the findings of the approach in terms of problems, their causes and improvement areas detected?

a. Definitely, I would not. I am not sure the approach would cover all quality concerns.
b. I have doubts about trusting the findings.
c. I can trust the findings to some extent and I would consider them in improving data quality.
d. Definitely, I would. I would immediately evaluate the findings revealed, and plan actions for data quality improvement.

34- How do you evaluate satisfactoriness of the approach proposed in general between scores 1 and 10? (1- Completely unsatisfactory, 10- Completely satisfactory)

① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩

35- Do you think there are deficiencies to fulfill or areas to improve regarding the approach proposed? Please state if any.
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36- What type of difficulties do you think your bank might experience in practical application of the approach proposed? Please state if any.
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*Thank you for participating our survey…*

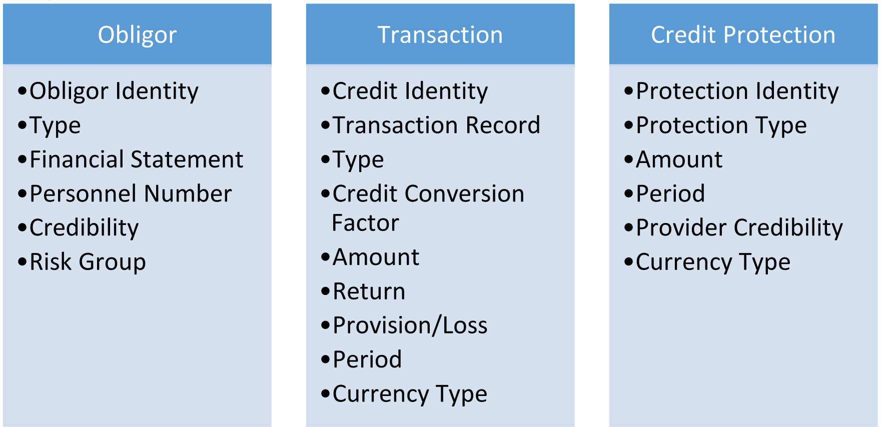
Please send e-mail to igunes@bddk.org.tr if you have any question.

## ***Appendix:*** *Summary of the Data Quality Assessment Approach*

The approach consists of four phases. These phases are definition, measurement, analysis and improvement of data quality.  The phases are executed iteratively. (Definition→Measurement→Analysis→Improvement→Definition). The phases are summarized with their outputs as follows.

### 1-Definition Phase

- Definition of data entities and their attributes
    - Obligors/Transactions/Credit Protections

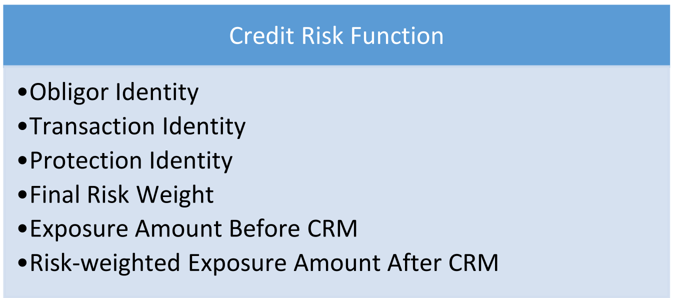


**Obligor**
- Obligor Identity
- Type
- Financial Statement
- Personnel Number
- Credibility
- Risk Group

**Transaction**
- Credit Identity
- Transaction Record
- Type
- Credit Conversion Factor
- Amount
- Return
- Provision/Loss
- Period
- Currency Type

**Credit Protection**
- Protection Identity
- Protection Type
- Amount
- Period
- Provider Credibility
- Currency Type

- 
    - Credit Risk Function (derived from obligor, transaction and credit protection relationship)



**Credit Risk Function**
- Obligor Identity
- Transaction Identity
- Protection Identity
- Final Risk Weight
- Exposure Amount Before CRM
- Risk-weighted Exposure Amount After CRM

- Identification of data sources used to obtain information about the attributes of the entities
    - Account Management System
    - Accounting System
    - Collateral Management System
    - Rating System
    - Risk Management System (fed by other systems)
- Definition data quality dimensions for each attribute of an entity
    - Uniqueness/Completeness/Accuracy/Consistency/Timeliness

### *Outputs of the Phase*

- Data entities and attributes
- Data quality dimensions

### 2-Measurement Phase

- Development of data quality metrics

    - Data quality metrics for each attribute given data quality dimension
- Selection data quality assessment techniques for measurement of data quality metrics
    - Primary key/secondary key analysis, column analysis, cross-domain analysis, domain analysis, semantic profiling etc.
    - Creation of queries related to data quality assessment techniques
- Development of key quality performance indicators (individual indicators)
    - Transformation of data quality metrics to key quality performance indicators
- Development of composite quality performance indicators
    - Determination of weights of individual indicators (equal/prioritized)
    - Derivation of composite indicators by weighted sum of individual indicator for each dimension
- Data quality assessment based on composite indicator results

***Outputs of the Phase***

- Composite indicator results
- Data quality assessment results

## 3-Analysis Phase

- Analysis of indicator results and data quality assessment results
- Detection of drivers causing poor data quality performance by assessing composite indicators

***Outputs of the Phase***

- Causes of data quality problems
- Attributes causing poor data quality

## 4-Improvement Phase

- Identification of improvement areas based on the causes of poor data quality
- Investigation of improvement techniques
    - Cost/benefit analysis
- Recommendation of a combination of improvement techniques
- Selection among the alternative techniques.

***Outputs of the Phase***

- Improvement actions decided
- Improvement techniques selected

# APPENDIX F: Curriculum Vitae

## CURRICULUM VITAE

### PERSONAL INFORMATION

Surname, Name: GÜNEŞ, Muhammed İlyas

Nationality: Turkish (TC)

Date and Place of Birth: 16 July 1985, Malatya

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### EDUCATION

| **Degree** | **Institution** | **Year of Graduation** |
|---|---|---|
| B.S. | METU Industrial Engineering | 2008 |
| M.Sc. | METU Information Systems | 2016 |

### PROFESSIONAL EXPERIENCE

| **Year** | **Place** | **Enrollment** |
|---|---|---|
| 2008-2013 | Proje Enerji Ltd. | Industrial Engineer |
| 2013-present | BRSA (BDDK) | Assistant Specialist |

### FOREIGN LANGUAGES

Advanced English

## TEZ FOTOKOPİSİ İZİN FORMU

**ENSTİTÜ**

Fen Bilimleri Enstitüsü □

Sosyal Bilimler Enstitüsü □

Uygulamalı Matematik Enstitüsü □

Enformatik Enstitüsü ☑

Deniz Bilimleri Enstitüsü □

**YAZARIN**

Soyadı : GÜNEŞ

Adı : Muhammed İlyas

Bölümü : Bilişim Sistemleri

**TEZİN ADI** (İngilizce) : DATA QUALITY ASSESSMENT IN CREDIT RISK MANAGEMENT BY A CUSTOMIZED TOTAL DATA QUALITY ASSESSMENT APPROACH

**TEZİN TÜRÜ** : Yüksek Lisans ☑ Doktora □

1. Tezimin tamamından kaynak gösterilmek şartıyla fotokopi alınabilir. ☑
2. Tezimin içindekiler sayfası, özet, indeks sayfalarından ve/veya bir bölümünden kaynak gösterilmek şartıyla fotokopi alınabilir. □
3. Tezimden bir (1) yıl süreyle fotokopi alınamaz. □

**TEZİN KÜTÜPHANEYE TESLİM TARİHİ :** ……………………