International Journal of Engineering Research and Technology.
ISSN 0974-3154 Volume 11, Number 4 (2018), pp. 621-636

http://www.irphouse.com

Master Data Management Maturity Model for the successful of MDM initiatives in the Microfinance sector in Peru

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Abstract

The microfinance sector has a strategic role since they facilitate integration and development of all social classes to sustained economic growth. In this way the actual point is the exponential growth of data, resulting from transactions and operations carried out with these companies on a daily basis, becomes imminent. Appropriate management of this data is therefore necessary because, otherwise, it will result in a competitive disadvantage due to the lack of valuable and quality information for decision-making and process improvement. The Master Data Management (MDM) give a new way in the Data management, reducing the gap between the business perspectives versus the technology perspective In this regard, it is important that the organization have the ability to implement a data management model for Master Data Management. This paper proposes a Master Data management maturity model for microfinance sector, which frames a series of formal requirements and criteria providing an objective diagnosis with the aim of improving processes until entities reach desired maturity levels. This model was implemented based on the information of Peruvian microfinance organizations. Finally, after validation of the proposed model, it was evidenced that it serves as a means for identifying the maturity level to help in the successful of initiative for Master Data management projects.

Keywords: Master Data Management, Maturity Model, Microfinance, Data Governance, Data management

1 INTRODUCTION

Microfinance institutions have generated a great impact on growth, Peru having the most favorable environment for financial inclusion worldwide (Microscopio Global, 2016). Likewise, microfinance systems experienced a growth of 13.12% in 2016 compared to 2015 (Association of Microfinance Institutions, 2016), representing a significant increase in customers, leading to more daily transactions and a large amount of data to process. Proper master data management is necessary to avoid redundant and inconsistent data, thus avoiding competitive disadvantages before other financial entities. Therefore, there is a need for a model in the microfinance sector which evaluates master data maturity levels, to take necessary actions in reaching desired levels. It is of vital importance to have adequate data management since the average cost of each lost or stolen record containing sensitive information (such as master data in organizations) is $141, resulting in an average loss of $3.79 million per year (Ponemon Institute and IBM, 2017).

Although master data management maturity models exist, they are not in line with the microfinance sector regulations, criticality and data volume (Computing, 2015). Recently, Marco Spruit and Katharina Piezka proposed a maturity model based on best practices, however the same authors state that few models were analyzed, and that more experts should be consulted to determine exact dimensions (Spruit and Pietzka, 2015). Oracle also developed a maturity model based on five key areas; however, these areas are more aligned to a technical framework (Oracle, 2013). In 2010, Dataflux clearly shows components of DMM in a service model, also focusing on the technological aspect (Dataflux Company, 2010). In that same year, IMN proposes a maturity model with a good basis, especially regarding levels, but with a high-level perspective. For this reason, we developed a robust maturity model based on previous model analysis, as well as international regulations and framework, which allows evaluating different areas of company processes, which we have denominated "Dimensions". We begin with evaluating data policies and management, providing a general context for organizations, which serves as support for adequate data integration, thus ensuring quality. Finally, the model evaluates monitoring and control of data management processes, in order to determine whether indicators, which measure evolution processes, exist and are adequately managed. The model has 14 criterions specifically, distributed in six dimensions and five levels of maturity based on CMMI, since it can be easily used in government processes or data management (Stanford University, 2011).

Our study is divided into 5 sections. Section 2 consists in describing the study and literature review based on master data management topic or frameworks, and data management maturity models. Section 3 describes steps for designing proposed maturity model levels and criteria, linking existing models, and comparing tables. Additionally, this section describes model evaluation processes. Section 4 describes model validation results from being applied in a case study. Finally, section 5 details research conclusions and results obtained from model application.

2 RELATED WORK

We decided on four approaches based on research and literature review: Data Management Maturity Models, Guidelines for Master Data Management, Applied Regulations in Master Data Management and Master Data Management Maturity Models.

Despite large numbers of maturity models related to data management, the most recent published contributions have been taken into consideration. In 2017, Rivera, Loarte and Raymundo focused on the microfinance sector and proposed a data management maturity model contemplating a series of requirements and criteria related to information security, data quality, principles, among others. Criteria must be fulfilled so organizations in this sector obtain objective diagnoses. Moreover, it is necessary to point out the works of Marco Spruit and Catalina Sacu, published in 2015, who studied complexities in realizing Data Warehouse projects, concluding the importance of a Data Warehouse maturity model to measure project management and progress. In 2016, Marco Comuzzi and AnitPatel implemented a maturity model focusing on Big Data, supporting its necessity due to poor technological management, taking organizational, technological and strategic aspects into account. The same year, Pedro Domingues, Paulo Sampaio, and Pedro M. Arezes presented the first attempt to standardize integrated management systems, which in turn allows comparing and evaluating integrated systems in different organizations through a maturity model, allowing organizations to evaluate integrated management systems and thus plan activities to avoid unnecessary resource wastes. Ampuero, Alfaro, Raymundo and Dominguez perceive positive changes in organizations with respect to data value, and in 2013 they designed a techno-organizational data management maturity model, based on 11 categories, which allowed organizations to ensure success in their initiatives and discipline.

In 2012, Boris Otto carried out a case study on master data architecture design and maintenance, applied in the Bosch organization, based on four approaches to architecture: analytical, transactional, coexistent and parallel, showing four ways to distribute and relate master data sources with local systems owned by businesses (Otto, 2012). Martin Hubert and other authors describe a reference model with an integral view of the life cycle of master data, including strategic, operational and tactical aspects, to provide more comprehensive support for analysis (Hubert, 2013). In an empirical study carried out the same year, Anders Haug managed to identify 12 barriers, which generate poor quality in master data management and frequency according to company size (Haug et al., 2013). In the same way, Dominic Gerardi emphasizes the importance of master data quality by conducting research oriented to the health sector, explaining the need to have specific responsibilities for maintaining master data, and that not properly managing relationships between data quality and master data will increase costs and complexities (Gerardi, 2017). Following the importance of data quality, studies by Bibiano Rivas used ISO 80001x0 clauses to develop service design for the exchange of master data among organizations, thus developing a data dictionary with master data terms; a communication protocol; an API to manage master data messages; and algorithms to measure data quality. Unlike previous studies, Rikka Vilminko not only identifies aspects related to quality, but also obstacles and problems, which organizations may encounter when developing a master data management initiative. The study identified 15 obstacles, which help understand key aspects of master data management in an organization (Vilminko, 2017). All contributions presented are useful to knowing what areas to take into consideration when designing a model or implementing a master data management solution in an organization.

In the financial sector, it is essential to show reliability both in daily transactions and in reports presented. In 2012, Ya. R. Nedumov mentioned that the biggest complication when managing master data is ensuring integrity, coherence and consistency. The contribution it provides is based on standardization techniques of regulatory reference information, which make it possible to fix data, identify duplicates and unify redundancies. On the other hand, in 2014, László Szívós considers that the means to achieving transparent presentations of financial statements focuses on the veracity and accuracy of master data and master files for proper presentation. This belief is reflected in his research, where he analyzes control procedures of data sources used by financial institution and introducing the indispensable task of an auditor. In summary, both investigations address aspects, which support achieving adequate master data management from a regulatory perspective.

Finally, the most recent Master Data Management Maturity Models were analyzed. In 2010, Sanjay Kumar mentioned that master data management program success was unlikely, so he proposed a model with six maturity levels, where each level included systems and actions that should be taken to reach the next level (Sanjay Kumar, 2010). That same year, Dataflux presented a maturity model divided into six layers, containing components related to technical, operational and administrative aspects in each. In this way, each component has capacities that will be increased based on maturity levels in which organizations are located (Dataflux, 2010). In 2013, Oracle proposed five key areas to evaluate the entire organization. Likewise, it made use of levels defined by CMMI, to ensure the correct evaluation by entities (Oracle, 2013). The most recent and well-known model for managing master data is MD3M, which has thirteen areas and sixty-five capabilities. It also provides a more specific approach to criteria considered by each process area.

Each presented model has different areas, criteria and levels to be evaluated, however all maturity models described have the same purpose, to determine master data management maturity levels.

3 MASTER DATA MANAGEMENT MATURITY MODEL

3.1 Bases

In order to define proposed model components, an analysis was made of six maturity models used in leading market organizations with high impact, providing a solid knowledge base, considering necessary aspects for evaluation of master data management in organizations. We have denominated these aspects dimensions. Each model has its own definition for dimensions; however, we have grouped those, which will be used, for our model.

- Policies: It is important to have policies in order to have an atmosphere of knowledge (Spruit and Pietzka, 2015). Data controls, security norms and policies must be established (Oracle, 2013). In an MDM initiative, stakeholders must adhere to organization policies (Dataflux Company, 2010). Data policies, standards and best practices should be developed, audited and applied (Stanford University, 2011). Organizations must have policies and procedures (ECM, 2009).
- Data Governance: Data governance imposes business policies for data standards within an MDM environment (Dataflux Company, 2010). Data management is transversally associated with business units (SanjayKumar, 2010). Maturity models are linked to data governance (Stanford University, 2011).
- Data Model: This is a key issue that deals with data and infrastructure (Spruit and Pietzka, 2015). Data models (Data flux Company, 2010) represent MDM designs.
- Data Integration: Systematic data integration is crucial for business (Spruit and Pietzka, 2015). Master data solutions should be used in data integrations between applications (Oracle, 2013). The reality of MDM is the integration of data (Dataflux Company, 2010).
- Data Quality: This aspect includes evaluation techniques (Spruit and Pietzka, 2015). Data quality is important (Oracle, 2013). Data quality affects MDM (Dataflux Company, 2010). Master data management must be synchronized with data quality (SanjayKumar, 2010). Parameters should be defined for acceptable data quality levels (Stanford University, 2011).
- Monitoring: Proactive monitoring for data quality control is crucial (Dataflux Company, 2010). Processes must provide feedback and monitoring (ECM, 2009).

Table 1: Dimension Comparison Matrix

MODELS	DIMENSIONES					
	Politics	Data management	Data models	Data integration	Data quality	Monitoring
MD3M (Spruit and Pietzka, 2015)	X		X	X	X	
Oracle (Oracle, 2013)	X			X	X	
DataFlux (Dataflux Company, 2010)	X	X	X	X	X	X
IMN (Sanjay Kumar, 2010)		X			X	
DG (Standford University, 2011)	X	X			X	
ECM3 (ECM, 2009)	X					X

Maturity models analyzed present different levels of maturity, with which organizations are properly categorized according to dimensions. In table 2, it can be seen that most models adopt CMMI levels, which pose five maturity levels.

- Initial: AdHoc or Chaotic processes, providing an unstable environment (IBM, 2007) (Stanford University, 2011). A first awareness has been raised to problems related to MDM at the operational level (Spruit and Pietzka, 2015).
- Managed: Process approach to projects and is often reactive (IBM, 2007). Individual measurements are carried out to solve individual problems. There is no connection with other units or projects. Operative (Spruit and Pietzka, 2015).
- Defined: Process characterized by organization and is often Proactive (IBM, 2007). The first collaborations take place at a tactical level (Stanford University, 2011). Awareness was created to encourage other initiatives (Spruit and Pietzka, 2015).
- Quantitatively Managed: Measured and Controlled Process (IBM, 2007). Best practices for MDM. (Spruit and Pietzka, 2015). Processes are defined at the tactical level (Stanford University, 2011).
- Optimized: Optimized MDM. Improved company efficiency. Tactical approach on the subject (Standford University, 2011).

After analyzing maturity model levels, we realized that CMMI has been used successfully in master data management models as well as data governance, due to easy adaptability.

Table 2: Level Comparison Matrix

MODELS	NIVELES DE MADUREZ				
	1	2	3	4	5
MD3M (Spruit and Pietzka, 2015)	Initial	Repeatable	Defined process	Managed and measurable	Optimized
Oracle (Oracle, 2013)	Marginal		Stable	Good Practices	Transformational
DataFlux (Dataflux Company, 2010)	Initial	Reactive	Managed	Proactive	Strategic development
IMN (Sanjay Kumar, 2010)	Initial	Isolated	Organized	Unified	Optimized
DG Stanford (Stanford University, 2011)	Initial	Managed	Defined	Quantitatively managed	Optimized
ECM3 (ECM, 2009)	Not managed	Incipient	Formative	Operational	Proactive

3.2 Model

We observed that models recur in some areas or dimensions, based on analysis carried out in point A, also emphasizing the importance of evaluating not only issues related to master data management, but also issues related to policies, data Governance, among others. For this reason, the proposed model consists of 6 dimensions and 14 evaluation criteria.

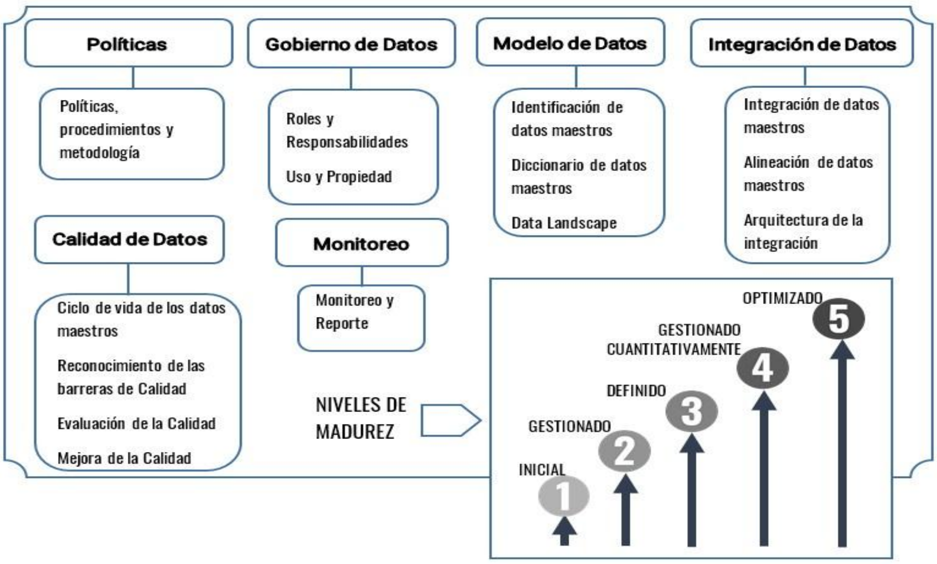

Figure 1: Graphic representation of the MDM Maturity Model aligned to the Microfinance Sector

3.2.1 Dimensions and Criteria

After comparing maturity models analyzed in point A, the following dimensions were identified, closely aligned with realities and needs of microfinance institutions in Peru.

- Policies: Microfinance institutions comply with different international regulations, which allow for an across-the-board evaluation throughout the organization, which is why we have considered it a key pillar in evaluating the extent to which policies are defined, formalized and implemented in terms of data management in those entities.

  Criteria making up this dimension are:

  - Policies, procedures and methods

- Data Governance: Definition of this domain involves evaluating roles and responsibilities defined in the organization, as well as data use and ownership.

  Criteria making up this dimension are:

  - Roles and responsibilities
  - Use and ownership

- Data Model: This domain is in charge of evaluating to what extent master data in the organization has been identified. It is also responsible for measuring master data models to serve as general data descriptions. Criteria making up this dimension are:
  - Master data identification
  - Master data dictionary
  - Landscape data

- Data Integration: This domain forms the central part of the model. It is responsible for identifying the extent to which controls are applied to data processing, combining them from different sources to manage extraction, transformation and loading mechanisms, considering business rules and legal requirements. In addition, this domain ensures alignment between businesses and IT, to subsequently implement data integration designs.

  Criteria making up this dimension are:

  - Master data integration
  - Master data alignment
  - Data integration designs

- Data Quality: This domain covers data life cycles. Starting by identifying organization quality barriers, followed by evaluation of data quality and improvement.

  Criteria making up this dimension are:

  - Master data life cycle

- Identification of quality barriers
- Quality evaluation
- Improvements in quality

- Monitoring: The purpose of this dimension is to identify to what extent master data management performance is monitored transversally in organizations, in order to measure and identify potential data problems.

  Criteria making up this dimension are:

  - Monitoring and Reports

Below is a table with evaluation criteria associated to each dimension in evaluating organizations.

Table 3: Model Evaluation Criteria

Dimension	**Criteria**
Politics	Policies, procedures and Methods. (Spruit and Pietzka, 2015) (Oracle, 2013) (Dataflux Company, 2010) (SanjayKumar, 2010) (Stanford University, 2011) (ECM, 2009)
Data governance	Roles and responsibilities (Dataflux Company, 2010) (SanjayKumar, 2010)
	Use and ownership (Spruit and Pietzka, 2015) (Oracle, 2013) (Stanford University, 2011)
Data models	Master data identification (Spruit and Pietzka, 2015) (Dataflux Company, 2010) (Stanford University, 2011)
	Master data models (Spruit and Pietzka, 2015)
	Landscape data (Spruit and Pietzka, 2015)
Data integration	Master data integration (Dataflux Company, 2010)
	Data alignment (Spruit and Pietzka, 2015)
	Data integration designs (Spruit and Pietzka, 2015)
Data quality	Master data life cycles (Spruit and Pietzka, 2015) (Oracle, 2013) (Dataflux Company, 2010)
	Identification of quality barriers (Spruit and Pietzka, 2015)
	Quality evaluation (Spruit and Pietzka, 2015) (Dataflux Company, 2010)
	Quality improvements (Spruit and Pietzka, 2015)
Monitoring	Monitoring and reports (Dataflux Company, 2010) (ECM, 2009)

3.2.2 Maturity levels

Based on analysis carried out in point A, we concluded that CMMI is easily adapted to data management models. This scheme was adapted to Master Data Management and microfinance needs. The following figure shows the established levels of the model, which helps identify maturity levels of organizations in terms of criteria evaluated:

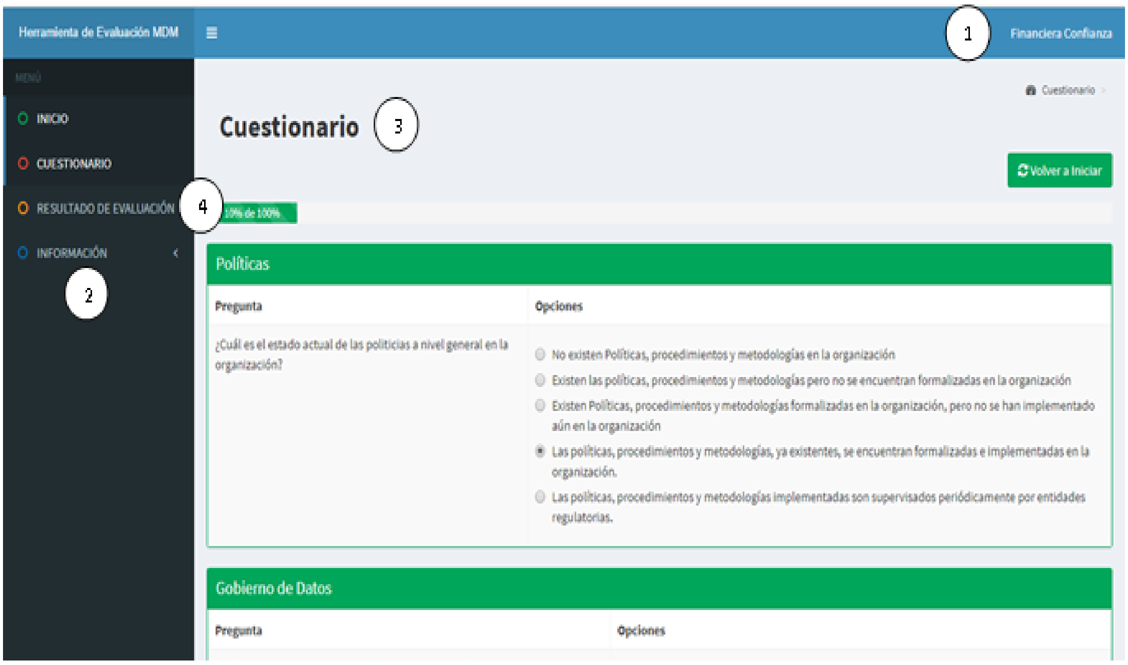

Figure 2: Evaluation Tool Questionnaire

3.2.3 Questionnaire

The questionnaire was developed under international standards, which provide information on proper master data management. In addition, three components in the Stanford Data Governance model were used in order to clearly identify differences between levels; therefore, each evaluation criterion must approve these three components in order to reach the next maturity level.

- Policies: This component ensures that evaluation criteria is measured based on documentation, formalization and definitions of processes and policies related to data management.
- People: This component ensures that evaluated criteria measures if roles and responsibilities have been defined. It also assesses awareness levels of people.
- Capacities: This component measures capacities of organizations

3.2.4 Evaluation Tool

A tool was implemented on a WEB platform in order to count on a consistent, easy-to-use evaluation tool. This platform can be accessed by microfinance entities previously registered in the database, so that they can submit the questionnaire and obtain results based on the status of their entity with respect to dimensions presented in the previous section. Main features of the tool can be seen in the following and referring to Figure 2:

1- One user per microfinance institution

2- The platform provides principal data regarding the model.

3- The questionnaire is found on the platform, allowing the user to save their progress and re-enter the platform to complete the questionnaire whenever they wish.

4- The platform shows evaluation results through a radial graph.

5- The tool compares microfinance institution results with the average result of all related entities having completed the survey.

Having answered the questions in the questionnaire, microfinance institutions will be able to visualize results according to previously presented dimensions and criteria, and their scores.

At the Model level

$$Score_{model} = \frac{\sum_{d=1}^{d} Score_{Dimension}}{D} \qquad (1)$$

At the dimension level

$$Score_{\text{dimension}} = \frac{\sum_{\text{cr}=1}^{\text{cr}} \text{Score}_{\text{criteria}}}{\text{cr}} \qquad (2)$$

At criteria level

$$Score_{criteria} = \sum_{c=1}^{c} pc * n \qquad (3)$$

D=number of dimensions

cr= Number of criteria

c= Number of components

pc = Importance of component

n= Maturity level

The following table shows score intervals that organizations must obtain to be categorized in a maturity level.

Table 4: Obtained score representation

Score	Maturity level
0 <Score<= 1	Initial
1 < Score<= 2	Managed
2 < Score<= 3	Defined
3 < Score<= 4	Quantitatively managed
4 < Score<= 5	Optimized

4 VALIDATION

It is very important to establish a degree of confidence in the model to guarantee its use and application. For this reason, a validation process was implemented based on the following points:

4.1 Planning

The validation scope was defined in the first stage, starting with microfinance institution selection and selection of necessary requirements to carry out the study and validate the maturity model. We considered evaluating all model dimensions presented, with their corresponding evaluation criteria, in order to achieve complete validation. The entity was given the pseudonym Microfinancing Company DVK for confidentiality and information protection issues. Microfinancing company DVK is a leading entity in the Peruvian microfinance sector, and its mission is to provide support to families with limited economic resources but with desires to improve their quality of life through different financial products. This entity is one of the few microfinance institutions that have a presence in all regions of Peru, with close to 500,000 clients, 2,000 employees and approximately 140 offices nationwide. Finally, to complete the planning stage, it was necessary to select those professionals who had experience in the microfinance sector and knowledge in master data management as well as international regulations.

4.2 Model application and diagnosis

The next step was based on evaluation of maturity model application to Microfinancing company DVK through the questionnaire. Once the questionnaire was completed, diagnoses were obtained, determining maturity levels in terms of dimensions and criteria defined, and represented in a matrix, which allowed distinction of results achieved (Table 4). These results were calculated based on formulas presented in the previous section.

Table 5: Level Comparison Matrix

Dimensión	Criterio	Resultado por Criterio	Resultado Final
Calidad de Datos	Ciclo de Vida de los Datos Maestros	1.40	1.75
	Reconocimiento de las barreras de calidad	2.2	
	Evalucación de la Calidad	1.6	
	Mejora de la calidad	1.8	
Gobierno de Datos	Roles y Responsabildiades	3.90	2.8
	Uso y Propiedad	1.7	
Integración de Datos	Integración de Datos Maestros	1.60	3.1
	Alineación de Datos	4	
	Arquitectura de Integración de Datos	3.7	
Modelo de Datos	Identificación de Datos Maestros	1.70	1.8
	Modelo de Datos Maestros	2	
	Data Landscape	1.7	
Monitoreo	Monitoreo y Reporte	1.30	1.3
Políticas	Políticas, Procedimientos y Metodologías	4.00	4

4.3 Results

Analysis of results is the last step in completing validation. Diagnoses obtained in the previous stage were analyzed in order to provide plans of action to improve maturity levels. In Figure 4, microfinancing company DVK showed a score of 4 out of 5 in the Policy dimension, being the most outstanding dimension of all, supervised constantly and even more so in the technological aspect, to corroborate information obtained in critical reports, through policy definition and formalization. Dimensions which obtained the lowest score were Data Quality, Monitoring and Data Models, reaching level two (Managed). This means that the microfinancing company DVK has identified concepts and requirements they need to carry out good master data management practices, however, they have not yet implemented most criteria. In addition, Data Integration was at a level 3 (Defined), which means that not only have the business rules and master data integration processes been defined, but a master data management solution has also been implemented to ensure the continuity of unique records based on an integration designs. Finally, the score achieved in Data governance is because the organization not only knows the need for definition of roles and responsibility, and using appropriate data, but also promotes other areas to use data properly in daily functions. The organization obtained an average score of 2.45, which translates into level three (Defined). Based on this fact, plans of action were outlined, in a summarized manner, to reach the next maturity level. First, organizations must implement data management policies. Second, they must establish roles and responsibilities, as well as instill awareness regarding data use and ownership. Next, organizations must identify the master data of each unit, define data models and implement master data integration processes. Finally, organizations must establish indicators for monitoring implemented processes.

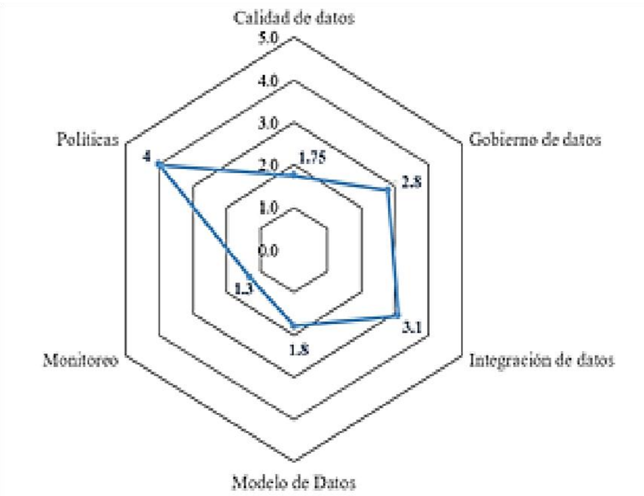

Figure 4: Radial graph representation of diagnosis

5 CONCLUSIONS

In this paper, a master data management maturity model was proposed for a microfinance sector in Peru, based on strict literature review, other similar models, as well as frameworks and international standards. The model includes closely related and coherent dimensions to perform a comprehensive analysis of organizations, consolidated with evaluation criteria in line with microfinance sectors. We also offer an online assessment tool where entities can access and complete a questionnaire used to subsequently obtain a corresponding diagnosis and their maturity levels.

The model was validated for a Peruvian microfinance institution, which made satisfactory use of the model evaluation tool, obtaining results through a radial chart and a detailed chart (Figure 3). Unlike other existing maturity models, our tool provides recommendations for entities to reach desired maturity levels in a later evaluation, while visualizing their progress and improvement in the maturity level obtained.

ACKNOWLEDGEMENTS

We thank the Peruvian University of Applied Sciences for partially financing this work and the opportunities offered to successfully complete the project.

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