**Improving Data Quality and Data Governance Using Master Data Management: A Review**

Sanny Hikmawati1, P. Insap Santosa2, Indriana Hidayah3

*Abstract*—Master Data Management (MDM) is a method of maintenance, integration, and harmonization of master data to ensure consistent system information. The primary function of MDM is to control the master data to keep it consistent, accurate, current, relevant, and contextual to meet different business needs across applications and divisions. If there are errors or mismatches on the stored data, it can reduce the data's accuracy and quality. MDM also influences data governance, which is related to the formation of roles, functions, and responsibilities of organizational actors in maintaining data quality. Poor management of master data can cause inaccurate and incomplete data, leading to stakeholders' decision-making errors. Based on these problems, the authors conducted a review of MDM implementation issues, a model to assess MDM's maturity and the person's roles in managing data quality. The review results show that obstacles and challenges to MDM implementation include no attempt to ensure the reliability of procedures, lack of roles and responsibilities in managing data, and lack of reliable data. To assess MDM maturity, organizations can use the Spruitz and Pietzka model, which covered all aspects of MDM in the organization and validated in research. MDM has a role in improving data quality and data governance through data owner, data stewards, and data governance council.

**Keyword**— *MDM, master data, data quality, data governance*

1. Introduction

Along with the development of information technology, reliable and trusted information system governance is necessary for every organization. Information systems must be trustworthy and dependable to ensure data quality, data consistency, data accuracy to support business decisions and become the foundation for future organizational growth [1].

Data is one of the valuable assets owned by an organization. One of the problems faced by many organizations is that data managed individually by various functional and structural units. There are differences in the data format used by each part of the organization, which results in data uniformity [2]. If the data is managed correctly, it will produce information that the organization can use for decision-making.

Increasing the amount of data is a challenge for organizational data management. It causes data quality issues that are very common in organizations today. Data quality remains a big problem for organizations which information systems spread over several different units or departments. Such information systems allow for the resolution of data quality problems such as duplication and inconsistency. By using Master Data Management (MDM) is expected to reduce these problems [3] [4].

1,2,3 Department of Electrical and Information Engineering, Faculty of Engineering, Universitas Gadjah Mada, Jln. Grafika 2, Kampus UGM Yogyakarta 55281 INDONESIA

(email: 1[sanny.hikmawati@mail.ugm.ac.id](mailto:sanny.hikmawati@mail.ugm.ac.id), 2[insap@ugm.ac.id](mailto:insap@ugm.ac.id), 3[indriana.h@ugm.ac.id](mailto:indriana.h@ugm.ac.id)

MDM is a series of application and technologies used to integrate and maintain master data. MDM can produce information that supports business decisions to increase organizational value. Poor control of organizational master data can cause errors related to the correctness and existence of data from each information system, whether it is master data, transactional data, or data analytics. Therefore, it is necessary to have a systematic approach so that the integrated data can produce accurate data, timeliness, secure data and a single point of reference.

MDM enables organizations to build and use a single point of reference to solve data completeness, accuracy, timeliness, and security. MDM can be applied across all industries and organizational data. The main function of MDM is to control the master data and keep it consistent, accurate, current, relevant, and contextual to meet different business needs across applications and units.

MDM provides a data governance model according to existing guidelines for good data and information management. Effective data governance can improve the quality, availability, and integrity of enterprise data by enhancing structured cross-organizational collaboration [5]. MDM encourages the roles and responsibilities of organizations in managing and using data to support good data governance. Organizations can implement good master data to be applied to all units in the organization.

The purpose of this paper is to the authors conducted a a review of MDM implementation issues, a model to assess MDM's maturity and the person's roles in managing data quality.

1. literature study
2. Master Data

Organization data consists of master data, transaction, and inventory data [6]. Master data is not only related to a customer, supplier, and material data. Employee data also classified as master data. Master data provides an interface for Business Intelligence (BI) by interacting with transactional data of various business areas such as sales, services, order management, purchasing, manufacturing, billing, accounts receivable, and accounts payable [7]. According to master data or reference data, every piece of information has a role in business processes. This information has been exchanged and processed on various networks by multiple users and groups around the organization [8]. Master data is a complement to BI by providing an excellent source of dimensional data.

Master data used in all organizational units. Thus, master data needs to be appropriately managed through master data management. To ensure good data governance, the organization must determine the function of the data owner and the role of data steward [9].

1. Master Data Management

MDM helps organizations standardize the definitions and attributes of data elements (customer, vendor, product, etc.). MDM can facilitate data sharing among all business functions, departments, and even different divisions across all information systems, platforms, and applications [10].

MDM creates a single data view of the targeted data domain. For example, master data management for customer records will refer to the "single truth" or "single customer view" of customer records. The process of making records by extracting, cleaning data from various corporate data sources is called Customer Data Integration (CDI). CDI is part of MDM. In various data sources inside an organization, MDM may provide solutions to solve quality problems like duplication, inaccuracies and incoherence.

The main process of MDM is profiling master data. The master data profiling feature aims to assess the state of data quality at various sources. Second, consolidating the master data into a repository and linking it with various existing applications. Third, cleaning the master data and enriching information. Fourth, synchronizing master data with organizational business processes with connected applications to support business intelligence and reporting systems [11].

MDM supports organizations integrating and sharing data in an accurate, timely, and consistent manner by implementing policies, services, and infrastructure. MDM guides the organization in creating master data.

1. Data Quality

Most of the world's databases have large amounts of data, are inconsistent, and are missing due to various factors that indicate insufficient data quality. Every year, low data quality costs governments and private businesses billions of dollars in income. Data quality problems are expected to cost companies up to 12% of their sales. Using the garbage in, garbage out principle for data analysis, processing, and management. If the input data quality is not good, the resulting output data will not be standard and will affect data accuracy [12].

Wang and Strong [13] have established 15 dimensions of data quality divided into four data quality classes. Redman [14] provided 51 data quality dimensions classified into nine data quality classes. Christen [15] summarized six data quality dimensions relevant to data matching in 2012 namely accuracy, completeness, consistency, timeliness, accessibility, and believability.

The UK Working Group of the Data Management Association International identified six dimensions to assess data quality in 2013. The data quality dimensions are accuracy, uniqueness, completeness, validity, timeliness, and consistency [16].

Based on [17], [18], and [19], data quality dimensions are divided into four categories, as shown in Figure 1.

Diagram

Description automatically generated

Fi*g.* 1*.* Data Quality Dimensions [17]-[19]

The barriers of data quality that have been identified in the literature are listed in Table I.

TABLE I. Data Quality Barriers

| Literature | Data quality barriers |
| --- | --- |
| Lee, at al [20] | 1. Lack of data quality responsibility 2. Missing the right technology 3. Procedures inadequate |
| Silvola [21] | 1. Poor data quality 2. Unclear master data definition 3. Incoherent approaches in data management 4. Lack of data maintenance process |
| Haug and Arlbarjon [22] | 1. Lack of delegation in charge of data maintenance 2. Lack of rewards to ensure the validity of the master data 3. Lack of regular control over data quality 4. Lack of competence from employees |
| A. Haug et al [23] | 1. Inefficient organizational procedures 2. Lack of training of data users 3. Lack of data quality measurements 4. Absence of an IT system for data management 5. Lack of data quality policies and procedures |

Issues related to data quality are increasingly important to analyze in an organization’s information system. Data quality is highly dependent on various scattered data sources that influence organizational decision-making [24].

1. Data Governance

The policies and procedures used to manage data in an organization are referred to as data governance. Data governance is a process that ensures the organization well works with data assets and ensures the organization’s data assets are well maintained. Organizations benefit from data governance because of data standardization, effective business policy formulation, and stakeholders’ role. Organizations may use data governance to align data management with business priorities, ensure regulatory compliance, and mitigate risk [25].

Many businesses have adopted big data in this age of digital transformation. Big data implementation necessitates a new collection of governance policies on which to base information management. Big Data governance refers to an organization’s accountability in information governance, stewardship, data definition, metadata management, master data management, usage standards, data life cycle management, risk, and cost control. Big Data governance includes optimization, privacy, and monetization policies following the objectives set. To control, ensure the availability, useability, integrity, accuracy, audit capacity of big data, the big data management system must establish policies, processes and standards [26].

MDM enhances data quality and develops data management processes by recording roles and responsibilities in data governance. MDM data governance consists of three components:

1. Managing critical data entities and main data objects.

2. Maintaining compliance with information policies.

3. Developing documentation.

Furthermore, MDM ensures responsibility for the maintenance of high-quality master data [27].

1. methodology

This study reviewed the effect of MDM on data quality and data governance. The review process uses the following methods:

1. Search articles

Search international journals like Scopus, Springer, IEEE, Sciencedirect, Emerald, and ACM Library. The keywords search for journal used are “master data”, “master data management”, “MDM”, “master data maturity management”, “data quality”, “data governance”. The keywords that are combined with “and” and “or”.

2. Articles selection

The articles chosen were articles that discussed MDM, data quality, and data governance in both the private and public sectors.

3. Analyze

The things that are analyzed are the MDM capability in the organization, master data management, the effect of MDM on data quality and data governance.

1. result

A. MDM Maturity Model

MDM program implies improved data quality. Several studies have made models for measuring MDM implementation’s maturity level through the Master Data Management Maturity Model (MD3M). MD3M is a measure of an organization’s ability to improve MDM sustainably. The purpose of assessing the maturity level of MDM implementation is to provide opportunities for organizations to evaluate the maturity level and benchmarks of MDM against other organizations [28]. The higher the MDM implementation value, the more optimal the organization will be in preparing and managing quality master data. Several comparisons of studies related to MD3M are described in Table II [29].

TABLE II. Comparison of MDM Maturity Models

|  |  |  |
| --- | --- | --- |
| Reference | Maturity Level | Dimension |
| Oracle [28] | 1. Marginal 2. Stable 3. Best Practice 4. Transformational | 1. Profiling data sources 2. Definition of data strategy 3. Definition of a data consolidation plan 4. Data maintenance 5. Data utilization |
| Spruitz and Pietzka  [29] | 1. Initial 2. Repeatable 3. Define Process 4. Manage and measurable 5. Optimized | 1. Data model 2. Data Quality 3. Usage and Ownership 4. Data Protection 5. Maintenance |
| Kumar [30] | 1. Ignorant 2. Initial 3. Isolated 4. Organized 5. Unified 6. Optimized | 1. No MDM awareness 2. Awareness of data quality issues 3. Strategy solving duplicate master data 4. Plan MDM initiatives 5. Defined MDM management support 6. Integration |

Oracle presents the MDM maturity model focusing on five areas: profiling data sources, definition of data strategy, definition of a data consolidation plan, maintaining of data, and utilization of data. The oracle model addresses the main focus areas of MDM. However, the oracle structure does not match the model’s maturity level because Oracle only provides a large area of interest and not detailed [29].

Kumar’s maturity model provides an overview and shows a good level of maturity. Kumar suggested awareness of data quality and consistency issues, strategy or roadmap solving duplicate master data, plan MDM initiatives, MDM management support, and integration. However, Kumar’s model does not clearly state the focus areas to be evaluated to assess the maturity level of MDM implementation [29] [30]. Kumar’s model only states the characteristics that must be met from each level to be assessed. It is suitable only for the first insight into the maturity of an organization’s MDM [29].

Spruitz and Pietzka defined the main topic and focus area of MD3M to cover all aspects of MDM that are important to the organizations. MD3M is divided into five main topics: Data model, Data Quality, Usage and Ownership, Data Protection, and Maintenance. These main topics are intended to assess the maturity of master data management. Those five main topics are divided into 13 focus areas. A data model’s focus area is on data definition, data model, and the data landscape. Data Quality focuses on assessments, impact on business, awareness of quality gaps, and improving data quality. The focus of Use and Ownership is data use, ownership, and access. Data protection focuses on data security or protection. Finally, the focus of maintenance is on data storage and life cycles [29]. This model’s implementation is customized to the organization’s need associated with master data by offering a model for evaluating maturity that has been validated in research [30]. To assess the implementation of MDM maturity, the organization can evaluate from which dimension are the main and least mature areas of concern. Organizations can use these evaluations to improve master data management and enable organizations to compare organizational efficiency with other organizations. Some researchers [31] [32], use the Spruitz model to assess the maturity level of an organization’s MDM implementation.

*B. The Effect of MDM on Data Quality and Data Governance*

Several studies have shown that MDM addresses data quality and data governance issues. The related research is shown in Table III.

TABLE III. MDM Solution

|  |  |
| --- | --- |
| Issues | Literature |
| Data Quality |  |
| * Duplication | [7], [9], [15] |
| * Accuracy | [7], [9], [15] |
| * Consistency | [7], [9], [15] |
| Data Governance | [7], [33], [34] |

With duplication, inconsistent and inaccurate data from various data sources, organizations need integrated data management. One of the factors driving the organization to implement MDM is the desire for consistency and accuracy organizational data. The MDM program’s core is consolidating multiple data sets representing master data objects such as customers or employees. These capabilities rely on metadata and data standards discovered through data profiling and discovery processes to parse, standardize, match, and resolve. Because the MDM program is intended to create good quality master data storage that is integrated, synchronous and consistent, the organization can perform data profiling and standardization and identify a set of master objects to assess the data’s quality. However, the organization must establish resolution and management data and analyze the master object relationship.

MDM defines data quality into the data management process through documented roles and responsibilities under data governance. To accomplish these tasks, the organization needs to establish team roles and responsibilities. The team formed is a collaboration between business people and Information Technology (IT) staff. On the other hand, successful MDM implementation depends on good data governance. The data governance program will also benefit the MDM program to strengthen the ability to manage all company information activities.

MDM is not only about technology, but all things needed to manage master data. Those are people, processes, and technology. According to [33], [34], to support the implementation of good data governance in implementing MDM, a business team and IT staff are needed. The roles and responsibilities in data governance are shown in Table IV.

TABLE IV. Roles and responsibilities organizational actor [33] [34]

| Role | Description |
| --- | --- |
| Data Owner | The data owner is in charge of the information presented. The data owner is also in order of managing and developing the data and making decisions about the data domain they own |
| Data steward IT | The data element standard format and implementation details are given. Determine any current or ongoing data quality criteria for data |
| Data Steward (business), information steward | Setting data standards and policies from a business perspective and defining objectives for data quality |
| Data governance council | Control the development and implementation of data governance |

Master data has an important role in an organization because it becomes a reference for data transactions and changes rarely occur. Data quality assurance must occur across the master data lifecycle for MDM implementation to be effective. Improving consistency and unclear roles and responsibilities to maintain data quality are significant challenges in managing master data. Therefore, it is necessary to guarantee the data quality in implementing MDM so that organizations do not face repeated risks in creating master data. The roles and responsibilities of organizational actors to manage master data must be documented and implemented based on the rules set by the organization. Good data quality and good data governance are the keys to success in implementing MDM.

*C. MDM Implementation Issues*

Several researchers conducted research related to the steps of MDM implementation in organizations. The study analyzes the steps organizations can take to implement MDM and support the success of MDM are shown in Table V.

TABLE V. Comparison of MDM Implementation Steps

| Literature | MDM Implementation Steps |
| --- | --- |
| [35] | 1. Identify master data flow (source and target system) 2. Identify data source and application that use it 3. Gather organizations metadata 4. Define master data model 5. Define characteristic MDM tool according to organization’s requirement 6. Combine data source to create master data 7. Collecting and maintaining metadata 8. Publish master data/ modify target application |
| [36] | 1. Identify organizations need 2. Identify organization’s master data and system that use it 3. Define MDM governance 4. Define process maintenance 5. Define data standards 6. Define future improvement for current data quality 7. Planning MDM architecture (application, data flows, data security and data privacy issues) 8. Training and communication for all stakeholders 9. Roadmap/ strategy for MDM development 10. Define MDM characteristic (user interface, workflow, data editing, reconciliation, integration) |

Joshi’s [35] process, especially in the first and second steps, recognized the second step suggested by Vilminko [36], namely defining the master data and system. However, Vilminko’s approach is related to organizational processes themselves, not only technology and information systems. Before focusing on operations and technology, criteria are needed to identify master data. In a large business, organizations must analyze whether data is shared across various business processes.

The fifth step, namely define data standards proposed by Vilminko, also has similarities with the steps suggested by Joshi, in the third and fourth steps. Defining standards data such as attributes, data types, constraints, and dependencies are important in MDM for maintaining data quality. Data models play a role in comprehensive reporting.

There are also other similarities namely define MDM characteristic. The two researchers proposed the functional and operational characteristics of MDM. What distinguishes the two is that according to Vilminko, the characteristics are not only related to technology but also the interaction between the needs of the organization, data set and technology. This, in contrast to the Joshi’s process, which focuses more on technology for MDM.

The comparison results above show that Joshi’s proposed process is too focused on technical matters, even though the challenges in developing MDM are related to technology and organization. The organization’s strategy and objectives in implementing MDM need to be analyzed as to how MDM can align with the organization’s business development.

There are several challenges in implementing MDM. These challenges explained as follows.

1. Lack of roles and responsibilities in managing data

The organization does not have a clear description of the duties and responsibilities of the data owner [9], [23], [37], [38]. Unclear roles and responsibilities of data owners can result in poor data quality. This is because the data owner is responsible for the data they own and ensures that the data is correct.

1. Lack of reliable data

Data is used in many applications. Organizations do not implement data integration used for the entire organization [21], [23], [37],[38].

1. There is no attempt to ensure the reliability of procedures

Organizations do not take data management-related problems seriously [2], [37], [38], [39]. These problems are related to technology and processes and people in charge of handling master data in the organization.

To support MDM implementation following organizational needs, organizations need to define clear roles, functions, and responsibilities in data governance. MDM encourages the formation and change of roles and responsibilities of organizational actors for data management and information systems [39].

In addition to the large amount of data scattered from various sources, unclear roles, functions, and responsibilities of personnel in the organization and the absence of adequate policies and procedures for data management are obstacles in making master data. A simple delegation of tasks to manage master data, therefore, affects master data quality and MDM implementation.

According to that explanation, the introduction of MDM has a significant impact on the roles and responsibilities of company and IT actors in the enterprise for data management. Yet, this linkage received little attention. Several studies conducted indicate the roles and responsibilities of organizational actors in supporting data quality maintenance and MDM implementation. However, these roles and responsibilities have not been managed and adapted to organizational needs.

1. conclusion

Based on the review results, it can be concluded that there is a relationship between data quality, data governance and Master Data Management. MDM can solve data quality problems through the MDM process, namely duplication, inconsistency and inaccuracy of data caused by data originating from various scattered sources. The consistency of the master data stored in the master data repository, on the other hand, is crucial to a successful MDM implementation. The organization can achieve the successful implementation of MDM by ensuring data quality throughout the life cycle of the master data.

MDM also influences data governance. MDM encourages organizations to improve data management by adjusting the roles and responsibilities of business actors and IT staff documented through data management. Data governance contains the roles, functions, and responsibilities of business actors and IT staff to support MDM implementation. It shows that MDM has a significant influence on roles, functions and responsibilities in an organization.

A clear delegation of roles, functions and responsibilities in data governance also impacts data quality because good data governance can maintain data quality.

The organization can assess data quality and data management through the MDM Maturity Model (MD3M). Organizations can measure the extent of their MDM management. The result of the MD3M assessment is the organization’s ability to carry out MDM. From these results, organizations can determine which things need improvement to improve data quality management and data governance.

Reference

1. B. A. Nugraha, R. W. Witjaksono, R. Mulyana, And F. R. Industri, “Analisis Dan Perancangan Master Data Management (Mdm) ( Studi Kasus : Pt . Kereta Api Indonesia) Analysis And Design Of Master Data Management (Mdm) Based Dama-,” Vol. 2, No. Mdm, Pp. 3282–3289, 2018.
2. R. Vilminko-Heikkinen and S. Pekkola, “Organizational issues in establishing master data management function,” Proc. ICIQ 2012 17th Int. Conf. Inf. Qual., no. Mdm, 2012.
3. S. Lerche, “Achieving customer data integration through master data management in enterprise information management,” 2014.
4. R. F. Smallwood, Information governance: concepts, strategies, and best practices. John Wiley & Sons, 2014.
5. Purnama, Indra, “Perancangan arsitektur manajemen master data, studi kasus PT Jaya Mandiri Gemasejati”.
6. Wieczorek, S., Stefanescu, A., and Schieferdecker, I., “Test Data Provision for Erp Systems”, in: Book Test Data Provision for Erp Systems, IEEE, 2008, pp. 396-403.
7. Master Data Management in Practice: Achieving True Customer MDM. Cervo, Dalton, Allen, Mark. [Wiley Corporate F&A]. Hoboken, N.J.: Wiley. 2011
8. ﻿The transverse information system: new solutions for IS and business performance, Rivard, François. 1-84821-108-2, 978-1-84821-108-7 Date: 2009 Page: 49 – 84
9. D. Loshin, “Master Data Management,” Master Data Manag., no. June, pp. 67–77, 2009.
10. ﻿P. Kumar, Master Data Management (MDM) – Strategies, Architecture and Synchronisation Techniques, 2015
11. Indrajani, “Master Data Management Model in Company: Challenges and Opportunity,” ComTech Comput. Math. Eng. Appl., vol. 6, no. 4, p. 514, 2017.
12. Lee, Y., Pipino, L., Funk, J., Wang, R.: Journey to data quality. The MIT Press (2009)
13. ﻿Wang, R. Y., & Strong, D. M. Beyond Accuracy: What Data Quality Means to Data Con-sumers. Journal of Management Information Systems, Springer, Vol.12., No.4 (1996), pp. 5-34.
14. Redman, T.C.: Data Quality. The Field Guide, Digital Press, p. 74 (2001).
15. Christen, “﻿Data matching: Concepts and techniques for record linkage, entity resolution, and duplicate detection”; pp 1-270, 2012.
16. DAMA UK Working Group, “The six primary dimensions for data quality assessment,” 2013.
17. F. Sidi, P. H. Shariat Panahy, L. S. Affendey, M. A. Jabar, H. Ibrahim, and A. Mustapha, “Data quality: A survey of data quality dimensions,” in 2012 International Conference on Information Retrieval Knowledge Management (CAMP), 2012, pp. 300–304.
18. P. Glowalla, P. Balazy, D. Basten, and A. Sunyaev, “Process-Driven Data Quality Management – An Application of the Combined Conceptual Life Cycle Model,” in 2014 47th Hawaii International Conference on System Sciences (HICSS), 2014, pp. 4700–4709.
19. C. Batini, C. Cappiello, C. Francalanci, and A. Maurino, “Methodologies for data quality assessment and improvement,” ACM Comput. Surv., vol. 41, no. 3, pp. 1–52, Jul. 2009.
20. Lee, Y.W., Pipino, L.L., Funk, J.D. and Wang, R.Y. (2006), Journey to Data Quality, MIT Press, Cambridge, MA.
21. Silvola, Risto, O. Jaaskelainen, H. Kropsu-Vehkapera, and H. Haapasalo, “Managing one master data – challenges and preconditions,” Ind. Manag. Data Syst., vol. 111, no. 1, pp. 146– 162, 2011.
22. A. Haug and J. Arlbjorn, “Barriers to master data quality,” J. Enterp. Inf. Manag., vol. 24, no. 3, pp. 288–303, 2011.
23. A. Haug, J. Arlbjorn, and Z. F, “Master data quality barriers: an empirical investigation,” Ind. Manag. Data Syst., vol. 113, no. 2, pp. 234–249, 2013.
24. N. K. Yeganeh, S. Sadiq, and M. A. Sharaf, “A framework for data quality aware query systems,” Inf. Syst., vol. 46, pp. 24–44, 2014.
25. Chamberlain, A. (2013), Using Aspects of Data Governance Frameworks to Manage Big Data as an Asset, a PhD thesis at University of Oregon.
26. ﻿Zarate Santovena, A. (2013), Big data: evolution, components, challenges and opportunities, a PhD thesis at Massachusetts Institute of Technology.
27. ﻿ E. Buffenoir and I. Bourdon, “Managing Extended Organizations and Data Governance,” in Digital Enterprise Design and Management 2013, Springer, 2013, pp. 135–145.
28. M. Spruit and K. Pietzka, “MD3M: The master data management maturity model,” Comput. Human Behav., vol. 51, no. October 2014, pp. 1068–1076, 2015.
29. K. Pietzka, “MD3M Master Data Management Maturity Model - Developing an Assessment to Evaluate an Organization’s MDM Maturity,” University of Utrecht, 2012.
30. P. Rishartati and A. G. Data, “Maturity Assessment and Strategy to Improve Master Data Management of Geospatial Data Case Study : Statistics Indonesia,” 2019.
31. F. G. Pratama, S. Astana, S. B. Yudhoatmojo, and A. N. Hidayanto, “Master Data Management Maturity Assessment: A Case Study of Organization in Ministry of Education and Culture,” 2018 Int. Conf. Comput. Control. Informatics its Appl. Recent Challenges Mach. Learn. Comput. Appl. IC3INA 2018 - Proceeding, no. Citsm, pp. 1–6, 2019.
32. Aditrya Rahman et al, “International Journal of Emerging Trends in Engineering Research Master Data Management Maturity Assessment : A Case Study of a Pasar Rebo Public Hospital,” vol. 7, no. 5, 2019.
33. Ventana Research, “Building Successful Master Data Management Teams,” 2007.
34. B. Otto, “Organizing Data Governance: Findings from the telecommunications industry and consequences for large service providers,” Commun. Assoc. Inf. Syst., vol. 29, no. 1, pp. 45–66, 2011.
35. Joshi, A., (2007). MDM governance: a unified team approach. Cutter IT Journal, Vol. 20, No. 9. 30-35.
36. R. Vilminko-Heikkinen and S. Pekkola, “Establishing an organization’s master data management function: A stepwise approach,” Proc. Annu. Hawaii Int. Conf. Syst. Sci., pp. 4719–4728, 2013.
37. H. A. Smith and J. D. McKeen, “Developments in Practice XXX: Master Data Management: Salvation Or Snake Oil?,” Commun. Assoc. Inf. Syst., vol. 23, 2008.
38. R. Vilminko-Heikkinen and S. Pekkola, “Master data management and its organizational implementation: An ethnographical study within the public sector,” J. Enterp. Inf. Manag., vol. 30, no. 3, pp. 454–475, 2017.
39. R. Vilminko-Heikkinen and S. Pekkola, “Changes in roles, responsibilities and ownership in organizing master data management,” International Journal of Information Management, vol. 47. pp. 76–87, 2019.