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A Practical Approach to Enhance Data Quality Management in Government: Case Study of Indonesian Customs and Excise Office

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Abstract

Background: The exponential data growth emphasises the importance of efficient information flow in organisations, especially in the financial sector. Data quality significantly influences decision-making, necessitating reliable Data Quality Management (DQM) frameworks. Previous studies propose DQM to maintain data quality through regulation, technology, measurement, evaluation, and improvement. Researchers highlight high-quality data benefits in private organisations but note the lack of improvement in data utilisation in public organisations. In Indonesia, data accuracy and quality are crucial for financial policies, with frequent reports of data inaccuracies in the Directorate General of Customs and Excise (DJBC), demanding standardised DQM practices. However, However, prior studies have yet to provide comprehensive and practical solutions to improve DQM practices. This study therefore aims to measure the DQM maturity, provide recommendations based on best practices, and formulate a practical strategy for improvements along with indicators tailored to the organisation, a topic that previous research has not explored.
Methods: This study falls under a mixed method approach (a quantitative study followed by a qualitative study) and employs a three-stage methodology. The authors conduct maturity assessment using Loshin model through an assisted enumeration from 5 key stakeholders followed by recommendations based on the Data Management Body of Knowledge (DMBOK) and strategy formulation from internal documents and interview.
Results: The data analysis yielded a DQM maturity score of 3.10, indicating a "defined to managed" level of maturity. Among eight components, only one receives a Managed level, two components are in the Defined level and the rest belongs to a Repeatable level. This study also proposes three strategies to bolster DQM by targeting 49 weak points, which will be progressively and sequentially implemented over a three-year period, using twelve possible solutions.
Conclusion: The study highlights the importance of efficient data flow, particularly in the financial sector, and suggests DQM for maintaining data quality. DJBC's import DQM level is assessed using Loshin's measurements, revealing areas for improvement through key DMBOK activities. Recommendations include data governance, strategic planning, and sequential DQM implementation. The study concludes by formulating a practical approach to be applied in a three-year span with ten indicators to measure success.

Keywords: Data Quality Management, Data Quality Maturity Model, Data Quality Strategy, Loshin, DMBOK

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I. INTRODUCTION

The exponential growth of data has heightened the importance of efficient information flow within organisations, particularly in the financial sector [1], [2]. Data has become a crucial tool for achieving business objectives, and its quality significantly influences an organisation's perspective and decision-making processes [3], [4]. To ensure high-quality data management within organisations, reliable frameworks and awareness become truly essential [5]. Á. Valencia-Parra et al. [6] propose the use of data quality management (DQM) to maintain data quality and reap its benefits, while DAMA International [7] advocates DQM as a set of activities related to data quality regulation, technology, measurement, evaluation, and improvement, tailored to meet organisational requirements and adopt high-quality methods or frameworks.

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A. Di Vaio et al. [8] further emphasise that proper utilisation of high-quality data leads to a five per cent increase in decision-making effectiveness in private organisations. However, the study posits that public organisations exhibit no significant advancements in data utilisation, primarily due to their incapacity to effectively harness data. In the context of Indonesia, the precision and quality of data play a pivotal role in supporting financial policies, fortifying revenue collection, and maintaining social stability—especially in the context of import and export data regulations, which serve as the foundation for customs and excise [9]–[13]. Previous research underlines the importance of data generated in customs and excise, not only in preventing smuggling but also significantly contributing to government revenue [14]–[16]. Despite historical successes, such as Britain's international trade benefiting from positive tariff and excise policies on emerging industries, Indonesia faces persistent challenges [11], [13], [17], [18]. For instance, the Indonesian government grapples with implementing effective data quality control to monitor tobacco excise and address illegal cigarette trade [10], [11]. In essence, the accuracy and accessibility of customs and excise data play a pivotal role in shaping economic and social dynamics in Indonesia [13], [19].

Critical for comprehending Indonesia's customs and excise, import trade data remains pivotal. Rahardja & Varela [20] note that the importation of intermediate inputs and capital goods enhances product quality and spurs economic diversification. Pratikto [21] further establishes a positive correlation between exports and imports, driven by the real effective exchange rate. Import policies, particularly impactful in sectors like food and beverage [22], play a crucial role in fostering industry growth and recovery. International trade, especially imports, significantly influences Indonesia's economy, contributing to export earnings, job creation, and technology transfer [23]. Sudarmawan [24] and Purba et al. [25] highlight the positive effects of imports, cautioning against imprudent management to prevent foreign exchange reserve depletion. Import policies are indispensable for sectoral support, exemplified by the food and beverage industry [22]. Indonesian import trade data thus emerges as a vital tool for informed decision-making and strategic formulation.

Ensuring the efficacy of DQM holds paramount importance for governmental entities, as it is instrumental in guaranteeing the reliability of data and fostering seamless system interoperability [26]. Within public administration, the attainment of high data quality (DQ) levels not only corresponds to enhanced service delivery but also establishes stronger relationships with citizens [27], [28]. Foundational to the integration of artificial intelligence in government, data readiness is assured through effective DQM [4], [29]. Stressing the imperative of accurate, complete, and consistent data—Li et al. [30] and Sanabria [31] emphasise the crucial role DQM plays. Kubler [32] underscores the significance of DQ, particularly in the context of successful open data initiatives. Xu Mao [33] further draws attention to the adverse repercussions of DQ issues on data analysis and decision support capabilities.

Currently, the Directorate General of Customs and Excise (DJBC) becomes the organisation-in-charge of customs and excise in Indonesia by managing Import and Export Trade Data. DJBC plays a significant role by enhancing economic resilience for fair and high-quality growth through fiscal policies [34]–[36]. Correspondingly, DJBC seeks to improve its Import Trade data value and utility to enhance organisational efficiency and productivity. Two specific units are tasked to tackle the issues: the Data Quality Management Section (DQMS) and the Data Analysis and Services Section (DASS). These units have a pivotal role in fulfilling three strategic goals in DJBC: (i) enhance the precision, consistency, accessibility, integrity, and confidentiality of data to ensure accuracy and privacy; (ii) enhance user satisfaction; (iii) optimise the quality of data analysis and presentation.

However, after reviewing internal documents and conducting preliminary interviews, the auhors find data inaccuracies and anomalies within DJBC, resulting in frequent requests for data modifications and pinpointing the absence of standardised DQM practices. Prior studies endeavour various methods to measure data quality and DQM, such as Loshin's Data Quality Framework, rule-based measurement, the CMMI Institute Data Management Maturity Model, Open Data Maturity Measurement, or the Task-Based Data Quality (TBDQ) [37], [38]. Pradnyana et al. [39] further mapped the data quality of exports at DJBC, yet the study did not consider DQM. Focusing on DQM, researchers administered the Loshin Model [40]–[45] as a means to measure DQM maturity level. Sebastian-Coleman [46] reassures that increasing DQM in an organisation requires a comprehensive strategy from known best practices and should be tailored to the targeted organisation to address five common challenges, from data to culture challenges.

Nevertheless, there is a dearth of comprehensive studies for DQM improvement [47], [48]. Previous studies have the propensity to measure organisational maturity and then provide recommendations based on best practices [39], [40], [42], [48]–[54], without looking at the *big picture*—organisation needs, resources, and strategies. This study therefore aims to measure the DQM maturity, provide recommendations based on best practices, and —as advocated by Král [55]—formulate a practical strategy for improvements along with indicators tailored to the organisation, a topic that previous research has not explored. For the case study, the authors select Import Trade data in DJBC as this organisation holds comprehensive and important data for the Indonesian government regarding customs and excise.

As such, this study proposes three research questions to address. **RQ1:** What is the maturity level of DQM Import Trade data in DJBC? **RQ2:** What remedies can be used to improve DQM in DJBC? **RQ3:** What is the possible practical approach to follow the recommendation? The paper is organised as follows: Section 2 provides the theoretical foundation of the research, Section 3 details the research methodology, Section 4 presents the data processing results and findings, and Section 5 concludes and offers implications for both theoretical and practical purposes.

II. LITERATURE REVIEW

A. Data Quality Management (DQM) in Indonesian Government

DQ ensures data meets its intended purposes and user expectations, necessitating high DQ to avoid risks associated with low-quality data. Implementing a well-planned data quality management programme outlines processes, participants, and tools to meet required quality standards [3]. Prioritising data quality in public service improvements, particularly in government sectors, becomes crucial due to its user-centric nature and rapid technological growth [47], [56]–[58]. DQM, however, measures and enhances data quality within organisations such as planning, implementation, and control activities to ensure data usability [7]. DQM includes DQ assurance and control, instilling confidence in meeting requirements and fulfilling quality standards [59].

DQM initiatives improve decision-making, data integrity, organisational control costs, and risk reduction [52], [60], [61]. Continuous and total DQM encompass validation, cleansing, integration, and applying product quality control principles to maintain reliable data assets for effective decision-making [62], [63] Employing a framework in DQM planning and measurement significantly enhances data quality [51], [64].

Regarding DQM in the Indonesian government, Sondita et al. [49] have conducted a similar study at the National Remote Sensing Data Bank, Rahmawati & Ruldeviyani [43] and Sabtiana et al. [41] also conducted their study at BPS-Statistics Indonesia, and Indriany et al. [45] complete their study at National Narcotics Board. These studies show that the agencies have yet to fulfil their targets in DQM, and these researchers have only proposed theoretical recommendations based on known frameworks without addressing *the elephant in the room*—implementing DQM in the organisation. Lucas [59], El Khatib et al. [65], and Sebastian-Coleman [46] have further highlighted that there are many challenges in implementing DQM for an organisation and require not only theoretical approaches but also practical ones.

B. DQM Maturity Model

Maturity models enable organisations to assess their competence in specific areas, assigning numerical scores or ranks to their performance [3], [42]. Redman [69] introduced the Capability Maturity Model (CMM) as a framework for enhancing organisational effectiveness, similar to Loshin's five maturity levels [3]. Ryu et al. [66] proposed a framework focusing on data structure management and quality. Kirikoglu [67] presented a scoring model for small-scale organisations to assess data quality, while Caballero & Piattini [68] concentrated on data quality issues in information systems. Table 1 illustrates the comparison among these models.

TABLE 1
MEASUREMENT MODEL COMPARISON

Method	Maturity Level	Dimension
Ryu et al. [66]	Initial, Defined, Managed, Optimised	Total Corporate Integration, Data Structure Quality Management, Maturity Stages
Kirikoglu [67]	Person, Dependent and Basic; Policies, Standards, and Procedures; Defined and stable; Managed and standardised; Continues improvement	Disciplined; Standard Consistent; Predictable; Continuously Improving
Caballero & Piattini [68]	Initial, Definition, Integration, Quantitative Management, Optimising	Data acquisition; Data product manufacturing; Data maintenance
Loshin [3]	Initial, Repeatable, Defined, Managed, Optimised	Data Quality Expectations, Dimensions of Data Quality, Policies, Procedures, Governance, Standards, Technology, Performance Management

Previous studies and practitioners, furthermore, successfully administered the Loshin method to determine DQM maturity levels [3], [40]–[45]. With all its merits, this study therefore administers the Loshin method for its comprehensive and adaptable dimensions—applicable to various organisations [42], [43]. As such, Loshin's Model provides a comprehensive framework to assess data quality management maturity across eight crucial dimensions:

1) *Data Quality Expectations*
Measures explicit and implicit data quality expectations aligned with organisational policies.
2) *Dimensions of Data Quality*
Emphasises classification of data quality components and their compatibility with expected measurements.
3) *Policies*
Evaluates various data types and sources contributing to data management complexity.
4) *Procedures*
Validates the existence and effectiveness of data management activities.
5) *Governance*
Measures participatory, collaborative, and monitored data governance.
6) *Standards*
Focuses on data standardisation for internal and external data exchange.
7) *Technology*
Involves implementation and technology usage within the organisation.
8) *Performance Management*
Emphasises performance in governance, stewardship, and data quality fit determination.

C. DQM Practical Solutions

Previous studies pinpoint that the Data Management Body of Knowledge (DMBOK) has the ability to become the bedrock of DQM improvement [42]–[45]. DMBOK remains a collection of best practices and provides recommendations curated from an increasingly diverse background [7], [42]–[45], [48], [50]. DAMA-International [7] further postulates 12 crucial steps that an organisation can take to enhance DQM, as depicted in Table 2. The authors based their recommendations on these steps as a means to improve DQM in DJBC.

TABLE 2
DQM PRACTICAL SOLUTIONS BASED ON DMBOK

ID	Solution	Description
DQM1	Defining High-Quality Data	Organisations must clearly define "quality data" to prioritise strategies that align with their objectives.
DQM2	Developing a Data Quality Strategy	The organisation must create a DQ strategy that aligns with its business goals, involving a business data steward to ensure a successful approach.
DQM3	Identifying Important Data and Business Rules	Assisting data organisations in analysing matrix interests and business rules to determine how data is most suitable for their operations.
DQM4	Conducting a Preliminary Data Quality Assessment	An initial assessment of data quality helps organisations understand the content and relationships within their data, which can be compared with DQ strategy rules.
DQM5	Identifying and Prioritising Potential Improvements	Using comprehensive profiling data and stakeholder discussions to identify and prioritise potential improvements.
DQM6	Setting Goals for Data Quality Improvement	Focus on improving data quality while recognising the positive impact of investing in DQ improvement.
DQM7	Developing and Deploying Data Quality Operations	Executing DQ programs to maintain and support data quality involves DQ analysts and data stewards.
DQM8	Managing Data Quality Rules	Maintenance of DQ standards and rules in the form of metadata is crucial, given the existence of rules and documentation related to DQM.
DQM9	Measuring and Monitoring Data Quality	Monitoring data quality rules and using to carry out DQM operational procedures.
DQM10	Developing Operational Procedures to Manage Data Issues	Developing and implementing SOPs to address issues arising from existing data, including diagnosis, problem formulation, and problem-solving.
DQM11	Establishing a Data Quality Service Level Agreement (DQSLA)	Establishing a DQSLA that outlines the organisation's expectations for responding to and improving data quality-related issues.
DQM12	Developing Data Quality Reporting	Creating reports on data quality conditions, including data quality scorecards, trends, SLA matrices, data quality issue management, team alignment with data quality policies, and the positive impact of data quality improvement activities.

III. METHODS

This study falls under a mixed method approach (a quantitative study followed by a qualitative study) and employs a three-stage methodology to address the research questions, illustrated in Figure 1.

A. Stage 1: Literature Study

In stage 1, the literature study, the authors aim to conduct a problem analysis and literature review to understand the context of this study thoroughly. This study then begins with analysing the problems in the DJBC to identify the problem gaps and root causes. After obtaining the problem gaps and root causes, the research questions can be mapped.

1) Problem Analysis

Regarding DQM, the authors pinpoint the research gap among previous studies: *lack of practical, applicable approaches* [39], [40], [42], [48]–[54]. Previous studies tend to stop their research after providing recommendations from known best practices. Thus, this study aims to address three areas: (i) measure DQM maturity, (ii) provide recommendations, and (iii) translate the recommendations into practical approaches.

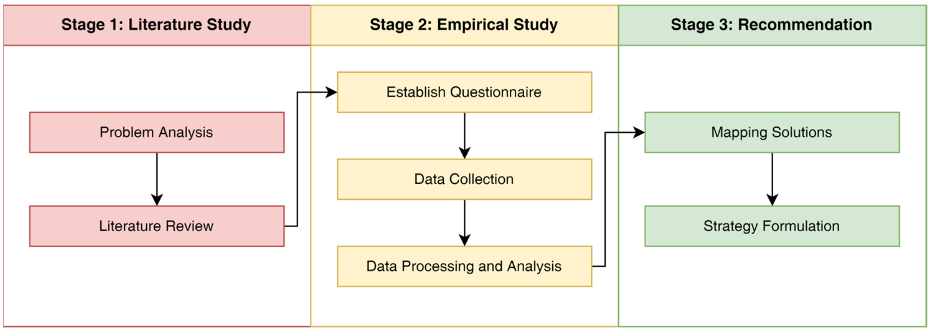

Fig. 1 Research methodology

2) Literature Review

Based on several studies in Table I, previous studies uncover myriad of frameworks to complete their studies. For instance, in measuring organisational maturity, researchers employ various models (see Table I). As for recommendations, researchers tend to use ISO:8000, ISO:9001, and DMBOK. All things considered; the authors then administer the framework model proposed by David Loshin as the chosen framework model for this study [3]. The authors also use DMBOK as the best practice model on which to base their recommendations for improving DQM in DJBC. The authors weigh internal documentation, legal standings, and interviews to implement the recommendations.

B. Stage 2: Empirical Study

1) Case Study: Indonesian Customs and Excise Office

In this study, we explore the intricate aspects of overseeing Import Trade Data within the Directorate General of Customs and Excise (DJBC) in Indonesia. DJBC, a pivotal actor in fostering economic resilience and equitable growth through fiscal policies, recognises the paramount importance of proficient data management [34]–[36]. Addressing challenges in data quality, DJBC has strategically instituted two units: the Data Quality Management Section (DQMS) and the Data Analysis and Services Section (DASS).

These units strive to achieve three strategic goals. Firstly, there is a commitment to enhancing precision, consistency, accessibility, integrity, and confidentiality of data to ensure accuracy and privacy (SG1). Secondly, the focus lies on elevating user satisfaction by enhancing the user experience through improved data quality. Finally, the organisation aims to optimise the quality of data analysis and presentation (SG3), recognising that data utility extends beyond mere collection to meaningful interpretation. The units also aim to comply with the DJBC's IT policies to provide insights into DJBC's comprehensive approach to DQM.

In this research, the authors obtained consent to publish the study's content, incorporating minor redactions and ensuring anonymity. Consequently, we anticipate that this endeavour will yield a more profound comprehension of the challenges within the Indonesian Customs and Excise Office.

2) Establish Questionnaire

For this research, the authors establish a questionnaire with 127 questions derived from 8 domains/components of David Loshin's DQM framework (see Table 3). Previous studies also use a similar questionnaire (derived from the Loshin framework) to measure the maturity level in their designated case study [40], [42], [43], [45], [48], [52], [70]. The authors thus decided to administer the original questionnaire from David Loshin's DQM framework to maintain the methodological continuity—minimising confounding variables and enhance the reliability of this study's results.

3) *Data Collection*

This stage continues with the data collection phase, where an assisted enumeration is used to collect data from 5 key stakeholders in DJBC with the authority of DQM. This approach draws a similarity with prior studies in using assisted enumeration [40], [42], [43], [48], [52]. These respondents include Project Manager, Data Quality Supervisors, and Data Engineers in DJBC. Questionnaires were employed to facilitate respondents in providing answers efficiently and saving time, enabling ease in data analysis. Regarding the scoring method, the authors administered the following rules: 1 for yes (implemented); 0 for no (not implemented).

TABLE 3
MEASUREMENT ITEMS

	Initial	**Repeatable**	**Defined**	**Managed**	**Optimised**
Expectation	EI1: Data quality activity is reactive EI2: No capability for identifying data quality expectations EI3: No data quality expectations have been documented	ER1: Limited anticipation of certain data issues ER2: Expectations associated with intrinsic dimensions of data quality associated with data values can be articulated ER3: Simple errors are identified and reported	ED1: Dimensions of data quality are identified and documented ED2: Expectations associated with dimensions of data quality associated with data values, formats, and semantics can be articulated using data quality rules ED3: Capability for validation of data using defined data quality rules ED4: Methods for assessing business impact explored	EM1: Data validity is inspected and monitored in process EM2: Business impact analysis of data flaws is common EM3: Results of impact analysis factored into prioritisation of managing expectation conformance EM4: Data quality assessments of data sets performed on cyclic schedule	EO1: Data quality benchmarks defined EO2: Observance of data quality expectations tied to individual performance targets EO3: Industry proficiency levels are used for anticipating and setting improvement goals EO4: Controls for data validation integrated into business processes
Dimensions	DI1: No recognition of ability to measure data quality D12: Data quality issues not connected in any way DI3: Data quality issues are not characterised within any kind of management taxonomy	DR1: Recognition of common dimensions for measuring quality of data values DR2: Capability to measure conformance with data quality rules associated with data values	DD1: Expectations associated with dimensions of data quality associated with data values, formats, and semantics can be articulated DD2: Capability for validation of data values, models, and exchanges using defined data quality rules DD3: Basic reporting for simple data quality measurements	DM1: Dimensions of data quality mapped to a business impact taxonomy DM2: Composite metric scores reported DM3: Data stewards notified of emerging data flaws	DO1: Data quality service level agreements defined DO2: Data quality service level agreements observed DO3: Newly researched dimensions enable the integration of proactive methods to ensure DQ as part of the life cycle
Policy	KI1: Policies are informal KI2: Policies are undocumented KI3: Repetitive actions taken by many staff members with no coordination	KR1: Organisation attempts to consolidate “single source of truth” data sets KR2: Privacy and limitations of use policies are hard-coded KR3: Initial policies defined for reacting to data issues	KD1: Tailored guidelines for establishing management objectives are established at line of business KD2: Certification process for qualifying data sources is in place KD3: Best practices captured by data quality practitioners KD4: Data quality service level agreements defined for managing observance of policies	KM1: Policies established and coordinated across the enterprise KM2: Provenance management details the history of data exchanges KM3: Policy-based data quality management KM4: Performance management driven by data quality policies KM5: Data quality service level agreements used for managing observance of policies	KO1: Automated notification of noncompliance to data quality policies KO2: Self-governing system in place
Procedure	PI1: Discovered failures are reacted to in an acute manner PI2: Data values are corrected with no coordination with business processes PI3: Root causes are not identified PI4: Same errors corrected multiple times	PR1: Ability to track down errors due to incompleteness PR2: Ability to track down error due to invalid syntax/structure PR3: Root cause analysis enabled using simple data quality rules and data validation	PD1: Procedures defined and documented for data inspection for determination of accuracy and validity PD2: Data quality management is deployed at line-of-business level as well as at enterprise level PD3: Data validation is performed automatically and only flaws are manually inspected PD4: Data contingency procedures in place	PM1: Data quality rules are proactively monitored PM2: Data controls are designed for incorporation into distinct business applications PM3: Data flaws are recognised early in information flow PM4: Remediation is governed by well-defined processes PM5: Validation of exchanged data in place PM6: Validity of data is auditable	PO1: Data controls deployed across the enterprise PO2: Participants publish data quality measurements PO3: Data quality management practices are transparent

TABLE 3 (CONTINUED)

	Initial	Repeatable	Defined	Managed	Optimised
Governance	GI1: Little or no communication regarding data quality management GI2: Information technology is default for all enterprise data quality issues GI3: No data stewardship GI4: Responsibility for data corrections assigned in an ad hoc manner	GR1: Best practices are collected and shared among participants. GR2: Key individuals from community form workgroup to devise and recommend data governance program and policies GR3: Guiding principles and data quality charter are in development	GD1: Organisational structure for data governance oversight defined GD2: Guiding principles, charter, and data governance management policies are documented GD3: Standardised view of data stewardship across the enterprise and stewardship program is in place GD4: Operational data governance procedures defined	GM1: Data governance board consisting of representatives from across the enterprise is in place GM2: Collaborative data quality governance board meets regularly GM3: Operational data governance driven by data quality service level agreements GM4: Teams within each division or group employ similar governance framework internally GM5: Reporting and remediation frameworks collaborate in applying statistical process control to maintain control within defined bounds	GO1: Data quality performance metrics for processes are reviewed for opportunities for improvement GO2: Staff members rewarded for meeting data governance performance goals
Standardisation	SI1: No data standards defined SI2: Similar data values represented in variant structures SI3: No data definitions	SR1: Data element definitions for commonly used business terms SR2: Reference data sets identified SR3: Data elements used as identifying information specified SR4: Certification process for trusted data sources being defined SR5: Data standards metadata managed within participant enterprises SR6: Definition of guidelines for standardised exchange formats (e.g., XML)	SD1: Enterprise data standards and metadata management SD2: Structure and format standards defined for all data elements SD3: Exchange schemas are defined	SM1: Certification of trusted data sources in place SM2: Master reference data sets identified SM3: Exchange standards managed through data standards oversight process SM4: Data standards oversight board oversees ongoing maintenance of internal standards and conformance to externally defined standards	SO1: Master data concepts managed within a master data environment SO2: Taxonomies for data standards are defined and endorsed SO3: Conformance with defined standards is integrated via a policy-oriented technical structure SO4: Straight-through processing is enabled for standard data
Technology	TI1: Internally developed ad hoc routines employed TI2: “Not invented here” mentality	TR1: Tools for assessing objective data quality are available TR2: Data parsing, standardisation, and cleansing are available TR3: Data quality technology used for locate, match, and linkage	TD1: Standardised procedures for using data quality tools for data quality assessment and improvement in place TD2: Business rule–based techniques are employed for validation TD3: Technology components for implementing data validation, certification, assurance, and reporting are in place TD4: Technology components are standardised across the federated community at the service and at the implementation layers	TM1: Automatic data correction guided by governance policies and defined business rules TM2: Impact analysis and what-if scenarios supported by dashboard and reporting tools	TO1: Nontechnical users can define and modify data quality rules and dimensions dynamically
Performance Management	MI1: Impacts are manifested and recognised long after failure events take place	MR1: Characterization of areas of impact of poor data quality MR2: Data profiling used to identify data failures in process	MD1: A framework for impact analysis is available MD2: Data quality service components are available and can detect early data errors	MM1: The data quality metrics are displayed in the management report MM2: Audit is based on compliance with rules related to data quality dimensions	MO1: Enterprise-wide performance can be improved through policy modification via rules environment

4) Data Processing and Analysis

In this study, the next critical phase involves data processing, utilising the three data collection methods to assess the maturity of DQM. Microsoft Excel processes the questionnaire data and measures DQM's maturity, similar to previous studies [40], [42], [43], [45], [48], [52], [70]. Suppose any discrepancies arise in the respondents' answers. In that case, we will seek confirmation to clarify their meanings and provide detailed explanations, ensuring a comprehensive analysis and one response per condition from all respondents.

In assessing the maturity level for each component, the calculation involves summing the values corresponding to each level of maturity. Each component has a maximum maturity level of 1, which is determined by averaging its overall characteristics. With five maturity levels, the highest possible score for one component is 5. To evaluate the maturity level of each component, the procedure entails adding the values assigned to each maturity level. Every component is assigned a maximum maturity level derived from the average of its overall characteristics.

For example, EI1 and EI2 are implemented, while EI3 provides no evidence of the implementation; thus, the value for this area is (1+1+0)/3 = 0.67 (see Table 4).

C. Stage 3: Recommendation

The final stage of this study commences by mapping solutions and formulating strategies for DQM improvements.

1) Mapping Solutions

Based on the result from the previous stage, the authors perform a mapping process to enhance DQM based on the current maturity level. The recommendation (based on DMBOK) addresses every indicator from the questionnaire where there is no evidence of the implementation. Thus, this study provides comprehensive recommendations to improve DQM in DJBC.

2) Strategy Formulation

Then, as advocated by previous research [71]–[73], the authors conduct a qualitative study using legal documents and an interview with the supervision from the head of Data Quality Management Section as the direct person in charge of DQM at DJBC, along with the team. In this process, the authors also align the recommendation with current strategies and policies. Thus, this study proposes a practical strategy translated from the previous recommendations based on the current organisation's needs and conditions. This study therefore holds practical approaches for DJBC to improve DQM swiftly.

IV. RESULTS

A. The Current Maturity Level of DQM (Address RQ1)

The authors process the data obtained from the four subject matter experts handling data quality at DJBC and then list the complete results in Table 4 and Table 5. In Table 4, the authors elaborate the data collection result while in Table 5 the authors depict the summary of data quality maturity measurement scores at DJBC. Based on Loshin's measurements, DJBC's Import Trade Data DQM level is currently at a defined-toward-managed level, with an average value of 3.10 out of a target value of 5 for all components. Five components reached the Repeatable level (Dimension, Policy, Procedure, Governance, and Technology), two components in the Defined level (Expectation and Performance Management), and a component scored the maximum level of Managed: Standardisation.

1) Repeatable Components

The value achieved by the Dimension component remains below the desired target (2.83 of 5.00), mainly due to insufficient documentation on fundamental data quality rules, data models, exchanges, and clusters within the organisation. Additionally, there is a lack of documentation for data values and formats from upstream to downstream. The documentation of data exchange activities and business impacts is critical for this dimension [52], [60]. This level also corresponds to the results from Setiadi et al. [40], Indriany et al. [45], and Wibisono et al. [52].

The Policy component, moreover, scores the lowest value (2.32 out of 5.00), attributed to the absence of underlying rules for DQM activities and data cleansing carried out solely based on employee Key Performance Indicators without any Service Level Agreements (SLAs). Indriany et al. [45] and Wibisono et al. [52] also uncover similar issues in their respective study cases, reaching a repeatable level in the Policy component. It is therefore essential to establish official rules governing DQM activities, and introducing SLAs can enhance data quality through importer profiling-based cleansing activities [43], [52].

Furthermore, the Procedure dimension lacks crucial activities, including formal procedures for DQM activity, data cleansing audit, and data exchange validation—2.83 of 5.00. Meticulous data cleansing for ensuring data integrity and accuracy, especially in diverse data types and applications, remains absent in DJBC. This condition is similar to the result from Setiadi et al. [40]. Improving data quality measurement and control procedures thus will enhance this component [7], [49], [54], [74], [75].

The Governance component also falls below the desired standard due to the lack of official records pertaining to data governance at DJBC (2.78 of 5.00). Indriany et al. [45] and Wibisono et al. [52] found a similar issue in this component as in DJBC's efforts to govern data are sporadic in nature, and certain aspects are treated as Key Performance Indicators. After the establishment of the database, data management activities primarily revolve around server maintenance, detecting input errors through automated procedures within the database, and modifying data as per the requests of individuals who manually input the data. Establishing a comprehensive data governance document thus becomes crucial for enhancing data quality [50].

The Technology component's value falls short (2.75 of 5.00) due to the lack of official regulations for data cleansing activities, insufficient data owner involvement, absence of visual monitoring or official reports on technology use in DQM, and undocumented business functions for data cleansing activities. In fact, Rahmawati et al. [43] and Indriany et al. [45] unveil similar issues in their studies with a similar value of 2.75. Albeit data cleansing activities have already been executed, it is essential to have complete documentation and agreement with data owners to participate in such activities [7]

TABLE 4
DATA COLLECTION RESULT

Level	Expectation		Dimensions		Policy		Procedure		Governance		Standardisation		Technology		Performance Management	
	ID	Score	ID	Score	ID	Score	ID	Score	ID	Score	ID	Score	ID	Score	ID	Score
Initial	EI1	1.00	DI1	1.00	KI1	0.00	PI1	1.00	GI1	1.00	SI1	1.00	TI1	1.00	MI1	1.00
	EI2	1.00	D12	1.00	KI2	0.00	PI2	1.00	GI2	0.00	SI2	1.00	TI2	1.00		
	EI3	0.00	DI3	0.00	KI3	1.00	PI3	0.00	GI3	1.00	SI3	1.00				
							PI4	1.00	GI4	1.00						
Value		0.67		0.67		0.33		0.75		0.75		1.00		1.00		1.00
Repeatable	ER1	1.00	DR1	1.00	KR1	1.00	PR1	1.00	GR1	0.00	SR1	1.00	TR1	1.00	MR1	1.00
	ER2	0.00	DR2	0.00	KR2	0.00	PR2	1.00	GR2	0.00	SR2	1.00	TR2	1.00	MR2	1.00
	ER3	1.00			KR3	0.00	PR3	1.00	GR3	1.00	SR3	1.00	TR3	1.00		
											SR4	0.00				
											SR5	0.00				
											SR6	1.00				
Value		0.67		0.50		0.33		1.00		0.33		0.67		1.00		1.00
Defined	ED1	0.00	DD1	0.00	KD1	0.00	PD1	1.00	GD1	1.00	SD1	1.00	TD1	0.00	MD1	0.00
	ED2	1.00	DD2	0.00	KD2	0.00	PD2	1.00	GD2	1.00	SD2	1.00	TD2	1.00	MD2	1.00
	ED3	1.00	DD3	1.00	KD3	1.00	PD3	1.00	GD3	1.00	SD3	1.00	TD3	1.00		
	ED4	0.00			KD4	0.00	PD4	0.00	GD4	1.00			TD4	1.00		
Value		0.50		0.33		0.25		0.75		1.00		1.00		0.75		0.50
Managed	EM1	1.00	DM1	0.00	KM1	0.00	PM1	0.00	GM1	1.00	SM1	1.00	TM1	0.00	MM1	0.00
	EM2	0.00	DM2	0.00	KM2	0.00	PM2	0.00	GM2	0.00	SM2	1.00	TM2	0.00	MM2	0.00
	EM3	0.00	DM3	1.00	KM3	1.00	PM3	1.00	GM3	0.00	SM3	1.00				
	EM4	1.00			KM4	1.00	PM4	1.00	GM4	0.00	SM4	0.00				
					KM5	0.00	PM5	0.00	GM5	0.00						
							PM6	0.00								
Value		0.50		0.33		0.40		0.33		0.20		0.75		0.00		0.00
Optimised	EO1	1.00	DO1	1.00	KO1	1.00	PO1	0.00	GO1	1.00	SO1	1.00	TO1	0.00	MO1	1.00
	EO2	1.00	DO2	1.00	KO2	1.00	PO2	0.00	GO2	0.00	SO2	1.00	TO2			
	EO3	1.00	DO3	1.00			PO3	0.00			SO3	1.00	TO3			
	EO4	1.00	DO4								SO4	1.00	TO4			
Value		1.00		1.00		1.00		0.00		0.50		1.00		0.00		1.00
Maturity		3.33		2.83		2.32		2.83		2.78		4.42		2.75		3.50

TABLE 5
DQM MATURITY LEVEL

Component	Indicator	Level					Total	Expectation	Result
		Initial	Repeatable	Defined	Managed	Optimised			
Expectation	18	0.67	0.67	0.50	0.50	1.00	3.33	5.00	Defined
Dimension	14	0.67	0.50	0.33	0.33	1.00	2.83	5.00	Repeatable
Policy	17	0.33	0.33	0.25	0.40	1.00	2.32	5.00	Repeatable
Procedure	20	0.75	1.00	0.75	0.33	0.00	2.83	5.00	Repeatable
Governance	18	0.75	0.33	1.00	0.20	0.50	2.78	5.00	Repeatable
Standardisation	20	1.00	0.67	1.00	0.75	1.00	4.42	5.00	Managed
Technology	12	1.00	1.00	0.75	0.00	0.00	2.75	5.00	Repeatable
Performance Management	8	1.00	1.00	0.50	0.00	1.00	3.50	5.00	Defined
	127						3.10		Defined

2) Defined Components

Insufficient documentation of data quality imports, lack of records on business implications of subpar data quality, and a need for countermeasures hinder the Expectation dimension's achievement of targets, similar to the findings from Rahmawati et al. [43] and Wibisono et al. [52]. With a score of 3.33 out of 5.00, DJBC can improve this area by providing detailed documentation outlining data expectations, quality standards, and potential consequences of inadequate data quality [4].

As for Performance Management, the value of this component falls below the target (3.50 out of 5.00) due to a lack of prioritisation by organisational leaders in DJBC. DQM activities are conducted but not officially documented. Efforts to minimise data input errors and automate data cleansing exist, but discussions and documentation of DQM activities need enhancement [7]. This finding corresponds to the results of Sabtiana et al. [41] and Rahmawati et al. [43].

3) Managed Components

The Standardised component exhibits the highest score among others, with a Managed level of 4.42, similar to Sabtiana et al. [41] and Rahmawati et al. [43]. This achievement is attributed to several factors, such as using appropriate standards in database creation, ensuring the availability of master and reference data, naming data entities based on business terms, and establishing a data exchange schema for various users. However, certain shortcomings persist, including the lack of standardisation in data element naming across databases within the same business process and inadequate documentation of metadata and data standards. These challenges can pose difficulties in data processing. In public services, data standardisation remains crucial for improving service quality, ensuring consistency, and facilitating effective decision-making processes [65], [76]. Therefore, aligning data element names and documenting data and metadata standards at DJBC stands paramount [40], [50].

4) Organisational Maturity Level

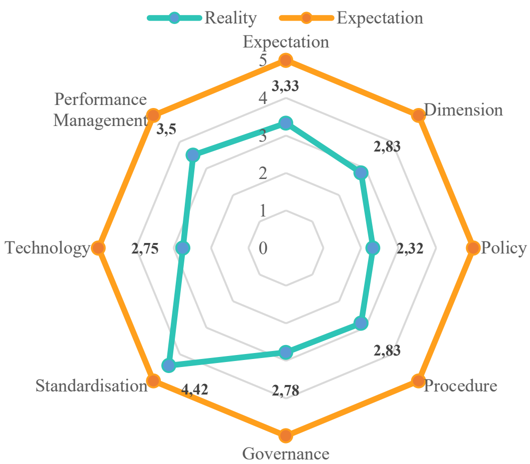

Fig. 2 DQM assessment in DJBC

According to Table 2, DJBC's DQM level is still at the defined level of 3.10, similar to the findings of previous studies by Sabtiana et al. [41] and Rahmawati & Ruldeviyani [43] in two different Indonesian agencies, where DQM values were 3.72 and 3.42, respectively. This defined level suggests that DJBC has implemented DQM activities using appropriate technology, considering the organisational needs that require these activities, and regularly holding meetings to discuss them. However, the absence of higher official regulations, related business impact, and documented implementation procedures and underlying rules remains a weakness in their DQM activities [3].

Figure 2 presents a radar chart to visualise the discrepancy between DJBC's expectations and actual condition. The chart reveals that the Standardisation component nearly meets the intended target, along with the Expectation and Performance Management components. Conversely, the other five components fall significantly short of DJBC's expectations, which aim for a Repeatable level.

TABLE 6
MAPPED SOLUTIONS BASED ON DMBOK

Level	Code	Condition	Solution
		Expectation	
Initial	EI3	Insufficient documentation exists concerning the expectations for DQ.	DQM1
Repeatable	ER2	There is a lack of specificity in identifying expectations for DQ and data value dimensions.	DQM3
Defined	ED1	The dimensions of DQ have yet to be identified and documented by DJBC.	DQM2
	ED4	A method for evaluating the business impact of flawed data has yet to be established.	DQM5
Managed	EM2	DJBC has yet to become acquainted with the business impact analysis of inaccurate data.	DQM3
	EM3	The EM2 analysis results are not deemed a priority for managing compatibility expectations.	DQM3
		Dimension	
Initial	DI3	There has been no categorisation or grouping of DQ issues.	DQM3
Repeatable	DR2	The general dimensions are inadequate for evaluating the compatibility of data values with DQ rules.	DQM8
Defined	DD1	Expectations for data value, format, and description have yet to be gathered.	DQM3
	DD2	These expectations have yet to be able to authenticate data values, models, and data exchange in line with established DQ rules.	DQM4
Managed	DM1	The dimensions of DQ have yet to be mapped to affected clusters within the organisation.	DQM5
	DM2	A report containing a matrix concerning DQ is not available.	DQM4
		Policy	
Initial	KI1	The policy has not been formalised yet.	DQM8
	KI2	The policy has yet to be documented.	DQM8
Repeatable	KR2	Privacy policies and constraints have yet to be identified.	DQM8
	KR3	The fundamental policy for addressing data issues has not been amended.	DQM8
Defined	KD1	There is an absence of guidelines for achieving management objectives within the business unit.	DQM2
	KD2	No certification process currently exists for DQ sources.	DQM7
	KD4	The DQ SLA collection has yet to manage compliance with a policy.	DQM11
Managed	KM1	Policies have yet to be formulated and coordinated throughout the organisation.	DQM6
	KM2	Historical data changes are not currently managed.	DQM8
	KM5	The DQ SLA is not currently utilised to oversee policy compliance.	DQM11
		Procedure	
Initial	PI3	The root cause of the issues remains unknown.	DQM10
Defined	PD4	Procedures for alternative data are lacking.	DQM10
Managed	PM1	Proactive monitoring of DQ rules is not taking place.	DQM1
	PM2	Data controls have not been developed to integrate into diverse business applications.	DQM4
	PM5	Data exchanges are not being validated.	DQM9
	PM6	The validation of data has not been subjected to audits.	DQM4
Optimised	PO1	Data controls have not been implemented across the organisation.	DQM4
	PO2	DQ measurements have not been published by the organisation.	DQM8
	PO3	Transparent DQ management practices have not been executed.	DQM12
		Governance	
Initial	GI2	IT-related concerns are not the only DQ problems.	DQM10
Repeatable	GR1	There is a lack of sharing and collection of data management experiences across the organisation.	DQM5
	GR2	The head of the working group responsible for designing and recommending policy programs and data governance is not from the organisation.	DQM1
Managed	GM2	Regular meetings have not been held by the data governance committee.	DQM1
	GM3	Data governance operations are not governed by service-level agreements (SLAs).	DQM11
	GM4	There is a disparity in the use of data governance frameworks by teams from each division.	DQM11
	GM5	There is no cooperation between reporting and improvement frameworks in applying statistical control processes to maintain predetermined limits.	DQM11
Optimised	GO2	There are no incentives for personnel related to data governance performance goals.	DQM5
		Standardisation	
Repeatable	SR4	There is no certification procedure for data sources at DJBC.	DQM9
	SR5	Metadata management is lacking in all DJBC units.	DQM3
Managed	SM4	The data standards oversight board has not supervised the maintenance of internal data standards and compliance with external data standards.	DQM1
		Technology	
Defined	TD1	There is no standard operating procedure for data inspection and DQ improvement.	DQM10
Managed	TM1	Data correction is not automatically based on applied governance and business rules.	DQM10
	TM2	Dashboards and reporting applications do not support impact analysis.	DQM12
Optimised	TO1	Non-technical users are unable to dynamically determine and modify DQ rules and dimensions.	DQM12
		Performance Management	
Defined	MD1	There is no framework in place for impact analysis.	DQM3
Managed	MM1	DQ matrices are not included in management reports.	DQM4
	MM2	Audits based on compliance with DQ dimension rules have not been conducted.	DQM2

I. DISCUSSION

A. Possible Solutions (Address RQ2)

Previous studies have proposed various suggestions to address the gap between results and targets. However, research conducted by Rahmawati & Ruldeviyani [43], Sunandar & Hidayanto [42], and Indriany et al. [45] lacked comprehensive and sequential guidance to bridge the gap, despite the importance of following a specific sequence according to the DMBOK. Conversely, Wibisono et al. [52], who also referenced DMBOK, provided more thorough recommendations for DQM based on the framework, incorporated into this study. For instance, this study employs the same method to remedy ED4 and DM1 using DQM5. Notably, Pradnyana et al. [39] evaluated data quality but overlooked the establishment of quality management procedures, which serve as the foundation for DQM [7]. Based on these findings, the authors have mapped recommendations for each component's gap, following DMBOK guidelines, as shown in Table 4.

As Table 6 provides the mapping to improve DQM in DJBC, Table 7 summarises the solutions used for DQM improvements. The twelve DMBOK solutions are used to solve a total of 49 items for DQM improvements. It remains essential to carry out all the activities in a sequential manner to ensure efficient implementation, with particular emphasis on three activities, specifically DQM3, which involves the identification of critical data and business rules. Despite the potential impact on primary business processes in the case of critical data issues, DJBC has not yet documented this item. Additionally, the database support documentation, including metadata, is currently non-existent and needs to be established [7].

Following this, the subsequent activity that demands significant attention is DQM8, which concentrates on managing the rules linked to DQM. It is crucial to create and document these rules as a government agency must comply with strict regulations. Thus far, DQM has primarily depended on Key Performance Indicators, calling for more comprehensive regulations to govern DQM [7]. The third activity that necessitates greater attention is DQM4, which focuses on DQM evaluation. The continuous improvement of all implemented processes remains critical [52]. Currently, evaluations are conducted only through meetings and incident reports without standardised guidelines.

TABLE 7
SUMMARY OF MAPPED SOLUTIONS

Activity	N	%
DQM1	5	10.20%
DQM2	3	6.12%
DQM3	7	14.29%
DQM4	6	12.24%
DQM5	4	8.16%
DQM6	1	2.04%
DQM7	1	2.04%
DQM8	7	14.29%
DQM9	2	4.08%
DQM10	5	10.20%
DQM11	5	10.20%
DQM12	3	6.12%
Total	49	100.00%

B. The Practical Approach (Address RQ3)

Subsequently, an implementation roadmap is established based on recommendations from discussions with DJBC data management responsible parties. Table 8 illustrates the implementation plan for DQM application recommendations.

Upon completion of the implementation plan for recommendations, a collaborative strategy was devised with the data management team at DJBC, aligning with DJBC's strategic plans and Internal IT Policies. Table 9 outlines strategies centred on DQM and success metrics, along with corresponding values resulting from implementing DQM data.

The roadmap introduces a mapped increase in the level of each category based on the implementation of each DQM activity from 1–12 and is considered in the DQM recommendation implementation roadmap.

In the first year, the focus is on implementing recommendations of DQM1 to DQM4 to lay the foundation for enhancing data quality. This involved identifying and gathering data quality factors, with particular attention to the Performance Management component, which exhibited the lowest gap compared to other components. In this period, DJCB would spectacle a significant improvement in the Dimension component from a Repeatable level to the penultimate level of Managed. This year, DJBC would expect to undertake improvements in Expectation

TABLE 8
A PRACTICAL APPROACH BASED ON DMBOK RECOMMENDATIONS

DQM	Condition	Practical Approach	Year		
			1	2	3
1	EI3	Establishing documentation related to expectations for DQ.	✓		
1	GR2	Identifying the organisational working group responsible for designing and recommending data governance policy programs and selecting its leader.	✓		
1	PM1	Proactively monitoring DQ regulations.	✓		
1	GM2	Holding regular meetings for the data governance committee.	✓		
1	SM4	Having the data standards oversight board supervise the maintenance of internal data standards and compliance with external data standards.	✓		
2	ED1	Identifying and documenting the dimensions of DQ.	✓		
2	KD1	Establishing guidelines for achieving management goals within the business unit.	✓		
2	MM2	Conducting audits based on compliance with rules related to DQ dimensions.	✓		
3	DI3	Categorising DQ issues.	✓		
3	ER2	Defining specific expectations for DQ dimensions and data value.	✓		
3	SR5	Determining the role of metadata management across all units within DJBC.	✓		
3	DD1	Defining expectations for DQ dimensions related to data value, format, and description.	✓		
3	MD1	Creating a framework for impact analysis.	✓		
3	EM2	Performing business impact analysis on defective or inappropriate data.	✓		
3	EM3	Formulating formal policies to make the results of impact analysis (EM2) a priority for compatibility expectation management.	✓		
4	DD2	Mapping DQ expectations to validate values, models, and data exchange using established DQ rules.	✓		
4	DM2	Generating a report containing a DQ matrix.	✓		
4	PM2	Designing data control integration into different business applications.	✓		
4	PM6	Performing data validation audits.	✓		
4	MM1	Providing DQ matrices in DQM reports to management.	✓		
4	PO1	Implementing data controls across the organisation.	✓		
5	GR1	Collecting and sharing data management experiences across the organisation.		✓	
5	ED4	Developing methods for assessing business impact.		✓	
5	DM1	Mapping DQ dimensions into impacted clusters within the organisation.		✓	
5	GO2	Offering rewards to staff in the form of meetings related to data governance performance goals.		✓	
6	KM1	Creating policies coordinated across the organisation.		✓	
7	KD2	Creating a certification process for DQ sources.		✓	
8	KI1	Formulating formal policies for DQM.		✓	
8	KI2	Documenting policies as regulations.		✓	
8	DR2	Measuring general dimension compliance of data values with DQ rules.		✓	
8	KR2	Defining and creating privacy policies and limitations.		✓	
8	KR3	Establishing basic policies for handling unresolved data issues.		✓	
8	KM2	Managing historical data changes.		✓	
8	PO2	Publishing DQ measures for the organisation.		✓	
9	SR4	Certifying data sources within DJBC.			✓
9	PM5	Validating data exchanges that occur.			✓
10	PI3	Identifying the source of problems.			✓
10	GI2	Stipulating in the rules that DQ problems are IT issues.			✓
10	PD4	Creating procedures for alternative data.			✓
10	TD1	Creating SOPs for data inspection and DQ improvement.			✓
10	TM1	Incorporating automated data correction activities based on applied governance and business rules.			✓
11	KD4	Creating a set of DQ SLAs for managing compliance with policies.			✓
11	KM5	Creating DQ SLAs for managing policy compliance.			✓
11	GM3	Operating governance operations based on service-level agreements (SLAs).			✓
11	GM4	Having teams from each division use the same data governance framework.			✓
11	GM5	Collaborating between reporting and improvement frameworks in implementing statistical process control to maintain established limits.			✓
12	TM2	Supporting impact analysis with dashboards and reporting applications.			✓
12	PO3	Conducting DQM practices transparently.			✓
12	TO1	Allowing non-technical users to dynamically determine and modify DQ rules and data dimensions.			✓

(Managed), Procedure (Defined), and Governance (Defined). However, the increase in the Policy component has yet to secure an improvement from the repeatable level. Overall, in this period, DJBC would improve their DQM Maturity Level from 3.10 to 3.88.

TABLE 9
SIMULATION OF DQM IMPROVEMENT

Component	Existing	Year 1					Year 2			Year 3			
		DQM1	DQM2	DQM3	DQM4	DQM5	DQM6	DQM7	DQM8	DQM9	DQM10	DQM11	DQM12
Expectation	3.33	3.67	3.92	4.75	4.75	5.00							
Dimensions	2.83	2.83	2.83	3.50	4.17	4.50	4.50	4.50	5.00				
Policy	2.32	2.32	2.57	2.57	2.57	2.57	2.77	3.02	4.55	4.55	4.55	5.00	
Procedure	2.83	3.00	3.00	3.00	3.67	3.67	3.67	3.67	4.00	4.17	4.67	4.67	5.00
Governance	2.78	3.32	3.32	3.32	3.32	4.15	4.15	4.15	4.15	4.15	4.40	5.00	
Standardisation	4.42	4.67	4.67	4.83	4.83	4.83	4.83	4.83	4.83	5.00			
Technology	2.75	2.75	2.75	2.75	2.75	2.75	2.75	2.75	2.75	2.75	3.50	3.50	5.00
Performance Management	3.50	3.50	4.00	4.50	5.00								
Average	3.10	3.26	3.381	3.65	3.88	4.06	4.08	4.12	4.41	4.45	4.64	4.77	5.00

In the second year, the emphasis shifted to implementing recommendations DQM5 to DQM8, concentrating on policies and efforts to enhance data quality, thereby improving the Expectation and Dimensions components to the fullest. In this period, DJBC would complete their improvement in the Expectation component after the first step (DQM5) and the Dimensions component in the final stage (DQM8). This period would also yield a major overhaul in the Policy component with multiple improvements from a Defined level after DQM7 and a Managed level after DQM8. The Procedure and Governance levels would improve to a Defined level in this period; however, Standardisation and Technology components would yet to receive major improvements. Finally, in this period, DJBC would improve their overall maturity level to Managed (4.41).

In the third year, the primary focus was implementing recommendations DQM6 to DQM12, centred on monitoring and enhancing DQM, leading to improvements in the Policy, Procedure, Governance, Technology and Standardisation components. This period would help DJBC see a complete improvement in DQM.

The authors further aligned the recommendation with the strategic approach to develop performance indicators for DJBC in their attempt to enhance DQM. This approach remains necessary as Král [55] insists that performance should be seen as a comprehensive, understandable, objective, and comparable criterion. The significance of implementing strategies in the public sector and their measurement is widely acknowledged [77]. The implementation of recommendations occurs in stages from DQM1 to DQM12, with the creation of strategies and performance measurement indicators guided by various factors.

Firstly, the level of public service satisfaction plays a crucial role, and the final stage reveals the outcomes of implementing all stages [55]. Moreover, the strategies devised must align with the organisation's predetermined strategic goals, thereby supporting the overall organisational objectives [78]. Priority assessment further focuses on factors with the greatest influence —DQM3, DQM4, and DQM8—. Although the execution of DQM8, DQM11, and DQM12 is planned for year 2 and year 3, performance indicators are evaluated from the first year onwards to monitor the progress resulting from implementing the recommendations.

From the internal documents and the interview, the authors choose three aligned strategic goals: Enhance the precision, consistency, accessibility, integrity, and confidentiality of data to ensure accuracy and privacy (SG1); Enhance user satisfaction (SG2); and Optimise the quality of data analysis and presentation (SG3). The authors further assessed the IT Policies and employ the following goals: Quality data analysis and presentation (BG1); Value-added quality control and internal supervision (BG2); and High satisfaction from customs and excise service user (BG3). Table 10 thus presents the proposed indicators to improve DQM, along with indicators and responsibilities.

C. Implications

This research holds considerable theoretical and practical significance. Theoretically, the efficacy of the Loshin method in comprehensively assessing the eight dimensions of DQM at DJBC has been confirmed, while the DMBOK has furnished rigorous suggestions and strategies to tackle the vulnerabilities within DQM. From a practical perspective, this study offers an encompassing overview of DQM within a government agency in a developing nation that oversees Import Trade data in customs and excise, thereby providing a benchmark for agencies both domestically and internationally to gauge DQM.

Despite the inherent challenges, the authors have adeptly devised practical approaches after a comprehensive examination of internal documents, legal frameworks, and interviews with key stakeholders. The recommendations proffered in this study hold the potential to greatly benefit DJBC in elevating its DQM practices, aligning them with contemporary standards and best practices in the field.

TABLE 10
KEY PERFORMANCE INDICATORS FOR DQM IMPROVEMENTS

DQM	Strategic Goal	IT Policy	Performance Indicator	Year			Unit
				1	2	3	
DQM1, DQM2, DQM3, DQM4, DQM5, DQM6, DQM7, DQM8, DQM10	SG1	BG1	Internal critical and priority data accuracy percentage at DJBC	80%	90%	99%	DQMS
			Accuracy percentage of external critical and priority data received by DJBC	80%	90%	99%	
			Percentage of data-related incidents and error reports from data users	1%	0,5%	0%	
			Data quality regulatory compliance index (scale of 5)	4,5	4,7	4,9	
DQM9, DQM12		BG2	Percentage of compliance and performance supervisors' reports on data findings	1%	0,5%	0%	
DQM12	SG2	BG1	Index of user satisfaction survey results (scale of 5)	4	4.25	4.5	DQMS
			Percentage of timely fulfilment of data service promises	80%	90%	95%	
DQM12	SG3	BG1	DJBC data usage percentage for effective data presentation	80%	90%	95%	DASS
DQM11		BG3	Percentage of catches and receipts from data analysis	80%	90%	95%	
			Percentage of data exchange effectiveness with external parties	80%	90%	95%	

D. Limitation

This study acknowledges certain limitations that have arisen. These include the restriction to a single measurement period, absence of comparative analysis, and reliance on a singular framework for deriving recommendations—DMBOK. It is important to note that the scope of this study is confined to Indonesia, which potentially restricts the generalisability of the findings to a broader demographic. Moreover, the practical implications may diverge in alternate agencies, as this study primarily serves as a *stepping stone* for more extensive research on the practical application of the DMBOK, aiming to enhance its relevance and efficacy in varied contexts.

II. CONCLUSION

The exponential growth of data emphasises efficient information flow in organisations, particularly in the financial sector. Data quality significantly influences decision-making processes. Researchers propose DQM for maintaining data quality, while DAMA International advocates DQM as activities tailored to meet organisational requirements. Prior study highlights the importance of high-quality data in private organisations, while public organisations face challenges in effective data utilisation. In Indonesia, data accuracy is vital, with reports revealing data inaccuracies and the absence of standardised DQM practices at DJBC. To address these issues, the Indonesian government introduced policies like One Data Policy and RPJMN. DJBC plays a crucial role in enhancing economic resilience through fiscal policies. This study aims to measure DQM maturity in DJBC and develop a practical strategy with tailored indicators. It fills the gap in practical recommendations for enhancing DQM within organisations.

Based on Loshin's measurements, DJBC's Import Trade Data DQM level is currently at a defined-toward-managed level, with an average value of 3.10 out of a target value of 5 for all components. Among eight components, only one receives a Managed level (Standardisation), two components are in the Defined level (Expectation and Performance Management) and the rest belongs to a Repeatable level (Dimension, Policy, Procedure, Governance, and Technology). DJBC further must fulfil 49 conditions across each component and level using DMBOK activities to achieve the target value of 5. The analysis of the 12 activities on DQM using DMBOK unravels that DQM3, DQM8, and DQM4 become the most critical areas that require attention. These activities address critical data identification and business rules, managing rules related to DQM, and DQM assessment.

To achieve optimal DQM, DJBC needs to establish data governance, prioritise the impact of DQM on business, create business impact documents for poor or incorrect data quality, establish SLAs for DQM activities, and set up procedures for monitoring the implementation of DQM rules at DJBC. The implementation of DQM activities will be carried out sequentially from DQM1 to DQM12, commencing in the first year and continuing through the third year.

This study also proposes three DQM strategies that will be assessed for success using ten indicators agreed upon by the data management team at DJBC for practical approaches. Ultimately, the Loshin method has proven to be effective in measuring the maturity level of DQM implementation at DJBC. The study recommends using DMBOK as a comprehensive guide for addressing weaknesses and planning DQM strategies.

Finally, in the future, the authors encourage researchers and practitioners to address this study's limitations by conducting research over multiple measurement periods, incorporating comparison groups, and exploring multiple frameworks for recommendations. Expanding the study to include data from multiple countries or agencies would improve generalisability. Additionally, implementing other frameworks in real-world settings can ensure practical relevance and effectiveness. Evaluating the long-term impact of DQM practices would also offer a more comprehensive understanding of DQM.

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