DATA QUALITY IMPROVEMENT USING QAFD FRAMEWORK: CASE STUDY OF FAST PAYMENT SYSTEM INFRASTRUCTURE

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ABSTRACT

Fast payment systems handle high transaction volumes and critical operations, making reliable data quality essential for reporting, analysis, and policy communication. This study aims to assess the data quality of Fast Payment System infrastructure applications using the QAFD (Quality Assessment Framework for Data) framework, focusing on five key dimensions. Data quality was evaluated through objective (quantitative measurements) and subjective (stakeholder perceptions) approaches across 34 variables. Objective assessments revealed Accuracy at 99.99%, Completeness (mandatory variables) at 84.41%, Uniqueness at 87.34-99.96%, and Currency & Timeliness both at 100%. Discrepancies appeared between objective and subjective results in Completeness and Uniqueness dimensions, highlighting metadata clarity and business rule alignment issues. This study provides empirical evidence of QAFD implementation in fast payment operations and recommends proactive data governance through enhanced metadata and validation mechanisms to ensure reliable reporting and institutional credibility.

***Keywords**: data quality assessment, QAFD framework, fast payment system, financial data governance, metadata enhancement, validation mechanisms*

I. INTRODUCTION

Data is a strategic asset for organizations. The systematic processing of data into information and knowledge is essential to support decision-making and enhance operational efficiency. In the financial sector, data growth is occurring very rapidly, particularly in Fast Payment System transactions. According to the Monetary Policy Report for the Third Quarter of 2025, the nominal value of Fast Payment System transactions increased by 32.34% to IDR 3,024.08 trillion, with a volume of 1,223.82 million transactions (year-on-year) [1].

This increase reflects the implications of digital transformation that drives the adoption of fast payment systems a mechanism enabling real-time transaction settlement available 24/7. In Indonesia, this acceleration aligns with the vision of the Indonesia Payment Systems Blueprint 2030, which targets the integration of the national digital economy and finance, as well as a balance between innovation and stability [2], [3]. However, the increase in transaction volume and speed amplifies the complexity of data management, particularly in the stages of integration, validation, and timeliness of availability.

Data quality becomes a primary determinant for the reliability of analysis and policy. Data in the fast payment ecosystem is generally high volume and high velocity for instance, Indonesia's Fast Payment System processes over 1,200 million transactions annually with peak loads exceeding 10,000 transactions per minute making it prone to incompleteness, inconsistency, or fragmentation across systems [4], [5]. This condition can reduce the accuracy of analysis and increase the risk of erroneous strategic decisions. Accurate, consistent, up-to-date, and timely data strengthens analytics, enhances monitoring effectiveness, and reduces operational risk [5], [6], [7].

The data quality of payment systems also affects public trust. Payment systems that ensure data integrity will strengthen the perception of service reliability and mitigate operational risks [8], as well as increase public trust in the digital payment ecosystem, both cognitively and emotionally [9], [10]. Therefore, improving data quality is not merely technical but also determines the legitimacy and social acceptance of the payment infrastructure [11].

The need for quality data is reflected in the publication of Payment System and Financial Market Infrastructure (PSFMI) Statistics, which serve as a means of communication and education for stakeholders, in line with Indonesia's membership in the Committee on Payments and Market Infrastructures (CPMI) since 2018 [12], [13]. This publication includes indicators on currency circulation, payment systems, and settlement systems, and emphasizes metadata consistency and validation referring to The Red

Book Statistics [14]. The availability of more complete and granular data also expands opportunities for econometric research, including analysis of digital transaction dynamics and their linkages to economic activity [13], [15].

In line with Bank Indonesia's plan to add Fast Payment System data to the publication starting in 2026, strengthening data quality becomes a prerequisite for maintaining statistical credibility and the effectiveness of policy communication [16]. Published data serves as a reference in assessing the performance and reliability of payment infrastructure [8], [16]. Data inaccuracies have the potential to degrade analysis quality and reduce public trust, given that public confidence heavily depends on the perceived reliability of the digital payment system [9], [10]. Therefore, improving data quality is a strategic step to ensure transparency and system stability in line with the central bank's mandate [8], [16].

Data quality in the Fast Payment System is crucial for developing predictive analytics, particularly for forecasting liquidity needs during periods of transaction surges [17]. Seasonal events like National Online Shopping Day (Harbolnas) have been shown to drastically increase transaction intensity in a short period, where payment gateway transaction volumes can increase up to threefold [18]. To address these analytical needs, measuring data quality using the Quality Assessment Framework for Data (QAFD) provides a structured approach to ensure data reliability and usability [7].

Although studies on data quality assessment have developed, research specifically addressing financial data quality remains limited [19]. More specifically, research on data quality assessment for daily fast payment system data is relatively scarce. This gap is relevant because daily data demands stricter quality controls compared to periodic reporting, especially concerning completeness, consistency, and timeliness. This research aims to measure, propose improvements, and suggest enhancements for the data quality of the Fast Payment System application at Bank Indonesia, as well as to identify the root causes affecting data quality. The urgency of this research lies in the need to ensure reliable data for internal reporting, institutional publications, regional economic analysis, and dissemination through official channels, given its direct impact on institutional credibility. Furthermore, improving data quality faces operational challenges: one ETL (Extract, Transform, Load) process from the Fast Payment System Application to the Enterprise Data Warehouse (EDW) takes approximately 3 hours daily, processing around 17 million transactions per day. This condition affects the timeliness, availability, and consistency of data used for analysis and reporting.

Literature indicates that specific frameworks for assessing financial data quality are still limited; one early reference is [20]. Furthermore, the application of financial data quality assessment in subsequent research is also reported to be limited and tends to be used for monthly reporting, with some studies only adopting partial dimensions [21]. This research is structured into five parts: (1) introduction, (2) literature review, (3) research methodology, (4) results and discussion, and (5) conclusion.

II. LITERATURE REVIEWS

A. Data Quality

Data is defined as a representation of real-world objects that have the capability to be stored, retrieved, and processed through software and communicated via networks [22]. In modern payment infrastructures, data quality becomes increasingly critical because real-time and high-volume transaction data require high levels of accuracy, consistency, and availability to support reliable analysis and policy decision-making. In the information management ecosystem, ensuring the quality of data assets is a fundamental aspect. Based on the Data Management Body of Knowledge (DMBOK) framework, Data Quality is positioned as a managerial function that encompasses planning, implementation, and control of data management techniques to ensure data availability and relevance for user needs [23].

User understanding of data quality and the factors causing its degradation is a fundamental aspect of information management. Decreased data quality is often triggered by temporal factors, where data becomes obsolete if not updated according to its volatility [20], [24]. Furthermore, data integrity is vulnerable to disruption during movement between applications or migration from sources to data warehouses through poorly validated ETL processes [25], [26]. To address this complexity, the literature proposes various evaluation approaches, both quantitative and qualitative, that define data quality through a set of specific attributes known as data quality dimensions [22], [24].

B. Data Quality Dimensions

Data Quality Dimensions refer to specific attributes of data used to assess its quality, where each dimension represents a distinct aspect and collectively reflects the overall level of data quality. The process of identifying relevant dimensions serves as a fundamental step initiating the assessment phase and serves as the foundation for data quality improvement strategies [22]. In their implementation, organizations need to establish specific dimensions because these characteristics are highly context-dependent, where the relevance and priority of each dimension can vary significantly between organizations and the types of data managed [22], [24]. The assessment focuses on five key dimensions: accuracy, completeness, currency, timeliness, and uniqueness, as proposed in the QAFD framework.

C. Data Quality Assessment Framework

Recent literature studies indicate the availability of various frameworks and methodologies in data quality management designed to assess and improve information quality [22], [27]. Key comparative frameworks include DAMA DMBOK, Total Data Quality Management (TDQM), IMF Data Quality Assessment Framework, and BCBS 239. In the framework selection process, the primary consideration is based on the methodology's focus and context of application relevant to this research namely data warehouse, financial data, or corporate data—as summarized in Table 1.

Table 1. Comparison of Frameworks with Specific Objectives

Framework	Main Focus of Application	Reference
DaQuinCIS	Corporate Information Systems	[28], [29]
DWQ	Data Warehouse Quality	[30]
proDQM		[31]
QAFD	Financial Data	[20], [21]
IMF DQAF		[32], [33]
BCBS 239		[34], [35], [36]

Based on the comparative evaluation presented in Table 2, this research establishes the Quality Assessment of Financial Data (QAFD) as the primary framework given its in-depth specificity to the financial data domain, particularly regarding operational data and payment system transactions. Unlike regulatory standards such as BCBS 239 or macro statistics like the IMF DQAF, QAFD offers a diagnostic approach capable of detecting anomalies in complex reference data [26], [27]. QAFD's methodological advantage lies in its ability to provide a holistic assessment through the integration of technical (objective) measurements and expert (subjective) perceptions to produce a multidimensional assessment and systematically identify quality gaps (gap analysis) [20], [26].

Table 2. Comparison of Data Quality Frameworks Focused on Financial Data

Criteria	QAFD	IMF DQAF	BCBS 239
Acronym	"Quality Assessment on Financial Data"	"International Monetary Fund Data Quality Assessment Framework"	"Basel Committee on Banking Supervision's, standard No. 239"
Data Context	Operational Financial Data	Macroeconomic Statistics	Banking Risk Data
Research Instruments	Database inspection, interviews, or questionnaires	Cascading Structure, ROSC (Report on the Observance of Standards and Codes), Self-Assessment	Self-Assessment, Supervisory Review, Key Risk Indicators
Diagnostic Approach & Improvement Direction	Diagnostic Gap Analysis	Improvements in the form of Technical Assistance, national statistical Capacity Building, harmonization of statistical methodology with international standards	Improvements in the form of recommendations for IT Infrastructure Transformation from manual to automation, Single source of truth to reduce data silos, Governance Enhancement

D. QAFD Framework

QAFD Framework is a methodology specifically designed to evaluate the quality of operational financial data with an approach that minimizes resources and measurement time. This framework operates through five systematic phases: (1) variable selection to determine data relevance in a financial context; (2) analysis to detect error patterns and business rules; (3) objective measurement using quantitative metrics; (4) subjective measurement based on the perceptions of business and data experts or qualitatively; and (5) comparison to identify discrepancies between technical assessment results and user views as a basis for improvement strategies.

The adoption of QAFD defines the main quality attributes used for assessment, namely accuracy, completeness, timeliness, currency, and uniqueness, as listed in Table 3 [20].

Table 3. Data Quality Dimensions

Dimension	Definition	Reference
Accuracy	The extent to which data is correct, reliable, and represents the true value (free from errors).	[20], [22], [37]
Completeness	The extent to which data has sufficient breadth, depth, and scope for the task at hand and is free from missing values.	[20], [21], [38]
Currency	The temporal proximity of the data value from the last update concerning the current value.	[19], [21]
Timeliness	Data availability when needed for operational use.	[21], [38]
Uniqueness	Data free from duplication.	[19], [37]

III. Research Method

The research methodology employs a mixed-methods approach, combining quantitative methods through database inspection of data obtained from the Data Owner (covering approximately 1 million during peak hour from 00:00 to 01:00 on the peak transaction day, Harbolnas, November 11, 2025) and qualitative methods through questionnaires distributed to respondents, namely units involved in data quality management or Data Quality Analysts. The QAFD framework is applied as the main methodology, with an additional recommendation phase to produce concrete and applicable improvement suggestions based on the assessment results of each data quality dimension. The research methodology flow is presented in Figure 1.

These improvement suggestions target the Data Owner and Data Quality Analysts. The Data Owner manages data from Payment Systems and Financial Market Infrastructure, including plans to incorporate Fast Payment System data into the 2026 publication. The recommendations serve as key considerations before data publication. The Data Quality Analysts handle work plans for enhancing data quality. The recommendations are formulated as proposed work plans for them.

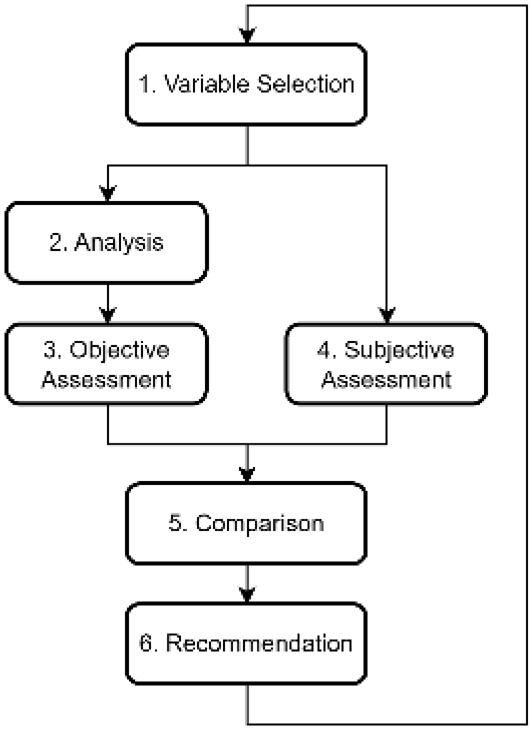

Figure 1. Research methodology developed from [20].

The questionnaire for the subjective assessment phase was developed based on the objective assessment results. It focused on variables with quality levels below 100% across the measured dimensions, creating assessment items that combine these variables with relevant QAFD data quality dimensions. Six respondents Data Quality Engineers, Quality Assurance personnel, and Testers with 3-5 years of experience completed the questionnaire. They used an operationally defined ordinal scale based on their practical knowledge of the data. The results were converted into quantified data quality scores and expected error rates, then compared with objective assessment findings during the gap analysis stage.

IV. Results And Discussions

A. Variable Selection

The selection of variables for the research was based on complete metadata definitions. A total of 60 variables from the Fast Payment System infrastructure serving as inputs to the Data Warehouse were included in the initial objective assessment to ensure comprehensive evaluation of all available data fields. This systematic process covered the entire data population efficiently. The results identified variables needing further analysis in subsequent stages.

B. Analysis

1) Accuracy Dimension

This dimension measures syntactic accuracy or the extent to which data resembles the data item domain or, in this case, the definitions in the data reference. Referring to the metadata provided by the Data Owner, there are 13 variables that have variable references. After calculations were performed as shown in Table 4, the percentage of the accuracy dimension for this data is 99.99% or close to 100%, or it can be said that it already refers to the reference.

Table 4. Accuracy Percentage

Variable	% Accuracy	Variable Reference
1. sender_bank_code	100.00	CL_Bank_Code
2. receiver_bank_code	100.00	CL_Bank_Code
3. status	100.00	CL_status_code
4. status_reason_code	100.00	CL_status_reason_code
5. transaction_by_service_type	100.00	CL_Service_Type
6. payment_channel_type	100.00	CL_payment_channel_type
7. part_sender_classification	99.97	CL_Classification
8. part_sender_type	99.97	CL_Type
9. part_receiver_classification	99.95	CL_Classification
10. part_receiver_type	99.95	CL_Type
11. proxy_type	100.00	CL_proxy_type
12. currency	100.00	CL_Currency
13. purpose_of_transaction	100.00	CL_purpose_of_transaction
Average	**99.99**	

2) Completeness Dimension

This dimension distinguishes between mandatory and non-mandatory variables. Mandatory variables must be filled, while non-mandatory ones are optional and may be left empty. Assessment checks for null or blank values in each record of mandatory variables [21]. Low completeness values for certain variables may limit their usability for analytical or monitoring purposes.

Based on metadata provided by Data Quality Analysts, these 26 variables have an average completeness percentage of 84.41, as shown in Table 5. Nine of the remaining 34 variables, confirmed by Data Quality Analysts, are optional variables or attributes (allowed blank): description, sender_hometown, receiver_hometown, sender_customer_type, sender_residential_status, receiver_customer_type, receiver_residential_status, proxy_type, and proxy_value.

Table 5. Completeness Percentage

Variable	% Completeness
1. transaction_date	100.00
2. settlement_date	100.00
3. sender_bank_code	100.00
4. receiver_bank_code	100.00
5. sender_acc_name	48.80
6. receiver_acc_name	48.67
7. sender_acc_number	53.74
8. receiver_acc_number	100.00
9. status	100.00
10. status_reason_code	100.00
11. transaction_by_service_type	100.00
12. amount	100.00
13. payment_channel_type	100.00
14. part_sender_classification	99.97
15. part_sender_type	99.97
16. sending_customers_id_number_hash	34.52
17. part_receiver_classification	99.95
18. part_receiver_type	99.95
19. receiving_customers_id_number_hash	9.15
20. currency	100.00
21. purpose_of_transaction	100.00
22. initiation_date_time	100.00
23. settlement_date_time	100.00
24. batch	0.00
25. message_id	100.00
26. acceptance_dttm	100.00
Average Completeness:	**84.41**

3) Currency Dimension

This dimension assesses data recency, measured by the time interval from data initiation to updating to the latest version. Because the data is transactional and implements ACID (Atomicity, Consistency, Isolation, and Durability) characteristics particularly atomicity and durability each transaction is processed in its entirety and stored permanently. ACID properties ensure that transaction data is processed reliably and stored permanently, enabling accurate and up-to-date data availability. Observations in Table 6 show a maximum update time of 1 second, well within the specified limit of 25 seconds (100% for the Currency dimension).

Table 6. Currency Dimension Sample

initiation_date_time	acceptance_dttm	Difference
00:11:41.000	00:11:42.000	1
00:19:42.000	00:19:43.000	1

4) Timeliness Dimension

This dimension assesses the extent to which data is available and accessible when needed to support task execution and decision-making, as well as its suitability for operational needs. Based on timestamp observations, daily transaction data is generated three times a day, making it available on the same day (H+0) until at least one day later (H+1). This condition indicates that data availability meets daily operational needs and reaches 100% in the timeliness dimension.

5) Uniqueness Dimension

This dimension is defined as data that has no issues related to duplicate data. Based on the provided metadata, the sender account (sender_acc_number_hash) should belong to the same sender ID (sending_customers_id_-number_hash). However, the uniqueness percentage for this variable was 87.34%, with the sample data shown in Table 7.

Table 7. Sample Uniqueness Dimension-Sender

sender_acc_number_hash	sending_customers_id_number_hash
d8691e287f3248bf31409ed9f543274f84361d90ab08059db5aeacac4c251743	220e40462946524f464084dc7a54af56fe46641ef018a13540a8304d2ce2aa01
	0b2d5f760667b2dc8c5c28e2a46df33e098a24a9d52b1e37ebcebdd83b8a0c6418497010cf0239547173031ea4b4f12d1c7713485993c7027b58f022536bb831

The recipient account (receiver_acc_numberhash) should have the same recipient ID (receiving_customers_¬id_number_hash). The uniqueness percentage for this variable is 99.96%, using the sample data in Table 8.

Table 8. Sample Uniqueness Dimension-Receiver

receiver_acc_number_hash	receiving_customers_id_number_hash
396d5c3edecf515e320c31283a24ca9a5a76ca847d993da4e2c3f922b6df2bbe	3973e022e93220f9212c18d0d0c543ae7c309e46640da93a4a0314de999f5112 caf8a00dd3938dbb1a433f45e0c42da82f278fcc79ec467a5c0540d6e8169ceb

C. *Objective Assessment*

In this phase, data quality evaluation and quantification are conducted based on the results of the data quality analysis in the previous phase. Prior to conducting the objective assessment, a sample of variables with a quality level below 100% was selected. Based on these criteria, the sample variables were selected, as presented in Table 9. After selecting the sample variables and summarizing the results of the data quality assessment percentage analysis based on the five dimensions, we converted the data quality quantification results for ease of interpretation, as shown in Table 10 [26].

Table 9. Percentage Of Objective Data Quality Assessment

\% Dimension / Variable	Accuracy	Completeness	*Currency*	Timeliness	Uniqueness	Average
part_sender_classification	99.97		100	100		99.99
part_sender_type	99.97		100	100		99.99
part_receiver_classification	99.95		100	100		99.98
part_receiver_type	99.95		100	100		99.98
sender_acc_name	48.80		100	100		82.93
receiver_acc_name	48.67		100	100		82.89
sender_acc_number_hash	53.74		100	100	87.34	85.27
receiver_acc_number_hash			100	100	99.96	99.99
sending_customers_id_number_hash	34.52		100	100	87.34	80.47
receiving_customers_id_number_hash	9.15		100	100	99.96	77.28
batch	0.00		100	100		66.67

Based on the percentage of data quality assessments for each dimension and mapped onto the assessment scale, the results are as shown in Table 11 [26].

Table 10. Objective Assessment Scale

Scale	*Points*	Data Quality
0-10%	10	Poor
10-20%	9	
20-30%	8	
30-40%	7	
40-50%	6	
50-60%	5	Mediocre
60-70%	4	
70-80%	3	
80-90%	2	
90-100%	1	
100%	0	Excellent

Table 11. Interpretation Of Objective Assessment

Dimension	sending_customers_id_number_hash	receiving_customers_id_number_hash	batch
Accuracy	-	-	-
Completeness	7	10	10
Currency	-	-	-
Timeliness	-	-	-
Uniqueness	2	1	
Average	**1.80**	**2.20**	**2.50**

D. *Subjective Assessment*

Perceptual assessment and cross-checking of sample variables sending_customers_id_number_hash, receiving_customers_id_number_hash, and batch were conducted with the six Data Quality Analysts and supported by the Data Owner. This ensured the variables' relevance to operational context and analysis needs. A subjective assessment form was then completed by the six Data Quality Analysts to evaluate these variables across the five data quality dimensions using a three-level ordinal scale (Poor/Low, Mediocre/Medium, Excellent/High). This scale was chosen to capture nuanced perceptions based on their expertise while maintaining simplicity for consistent responses, in line with the QAFD framework approach to subjective evaluation [20], [26]. The collected data was then analyzed, and the data quality quantification results were converted for easy interpretation, as presented in Table 12.

Table 12. Subjective Assessment Scale

Expert Opinion	Points
Poor (Low)	10
Mediocre (Medium)	5
Excellent (High)	0

Based on the percentage of data quality assessments for each dimension and mapped onto the assessment scale, the results are as shown in Table 13 below.

Table 13. Interpretation Of Subjective Assessments

Dimension	sending_customers_id_number_-hash	receiving_customers_id_number_hash	batch
Accuracy	0	0	0
Completeness	5.625	5	2.5
Currency	0	0	0
Timeliness	0	0	0
Uniqueness	6.25	2.5	-
Average	2.96875	1.875	0.625

E. Comparison

Based on Table 14, which compares the results of objective and subjective assessments, the accuracy, currency, and timeliness dimensions show a difference of 0, indicating alignment. In the currency dimension, the sample of daily Harbolnas transaction data for November 11, 2025, which is part of the fourth quarter of 2025, was deemed up-to-date for the research period of December 2025-January 2026 by Data Quality Analysts, with confirmation from the Data Owner, thus achieving a score of 100%. Consistent with this, in the timeliness dimension, the availability of data prepared according to operational requirements for reporting for the fourth quarter of 2025, which is generally conducted in January-February 2026, was also scored 100%.

Table 14. Objective-Subjective Measurement Differences

Dimension	sending_customers_id_number_hash	receiving_customers_id_number_hash	batch
Accuracy	0.000	0.0	0.0
Completeness	1.375	5.0	7.5
Currency	0.000	0.0	0.0
Timeliness	0.000	0.0	0.0
Uniqueness	-4.250	-1.5	0.0
Average	-0.575	0.7	1.5

Meanwhile, for data where the comparison result of the assessments is positive or above 0, it means that the data measured according to the objective assessment results in poor data quality or requires improvement, but according to the subjective assessment, the data quality is quite good, meaning that the data quality does not significantly affect decision-making or work processes. This occurred in the variable sample for the Completeness dimension.

The results of confirmation with the Data Owner and Data Quality Analysts indicate that the batch variable was previously used as information for the ETL batch process. Currently, data is available in real-time through the portal, so the batch variable may be empty (blank). Additionally, the sending_customers_id_number_hash and receiving_customers_id_number_hash variables may also be empty under certain conditions. In the future, metadata adjustments are needed to explain that these variables are not mandatory (allow empty) to avoid misinterpretation in the completeness dimension assessment.

Furthermore, for data where the comparison result of the assessments is negative or below 0, it means that the data measured according to the objective assessment results in good data quality. However, according to the subjective assessment, the data quality is quite poor, meaning that further improvement is needed. This occurred in the sending_customers_id_number_hash and receiving_customers_id_number_hash variables for the Uniqueness dimension.

The results of confirmation with the Data Owner indicate that findings related to sender accounts and receiver accounts associated with multiple IDs need to be followed up through further investigation, although functionally they are still in accordance with the operational needs of the payment system. For receiver accounts, this condition is suspected to be influenced by the operational characteristics of the Fast Payment System, where one account may have several derivative accounts (virtual accounts), thus requiring metadata adjustments, particularly data quality rules, so that the relationship structure is clearly documented. Meanwhile, for sender accounts associated with more than one ID, the initial suspicion points to the less-than-optimal validation process by Payment System Participants, so strengthening the validation mechanism and standardizing data entry are recommended steps to prevent potential duplication in the future.

Further confirmation with the Data Owner also explains the difference in variable selection between objective and subjective assessments. The variables sender_acc_name_hash, receiver_acc_name_hash, and sender_acc_number_hash may be empty (blank) under certain conditions related to transaction_by_service_type, particularly when the transaction is only for information request (account enquiry) so that the sender's name or account is not required to be filled. In this regard, the Data Owner plans to improve metadata to clarify the characteristics of variable filling and make it a reference for Data Quality Analysts in conducting data quality assessments. Additionally, the Data Owner asserts that variables with a quality level above 99.95% or an error rate below 1% were not selected as samples because they are close to perfect values and are within the operationally acceptable quality threshold, thus not requiring further analysis.

F. Recommendation

Prioritized Data Quality Improvement Recommendations: High-priority actions for Completeness (84.41%) and Uniqueness (87.34-99.96%) include immediate metadata updates documenting "allow empty" conditions for batch, sending_customers_id_number_hash, and receiving_customers_id_number_hash variables, supported by standardized templates and Data Quality Analyst training. Medium-priority cross-dimensional efforts focus on clarifying main/derivative account relationships, educating Fast Payment System Participants on sender account validation to prevent ID duplication, and implementing validation rules with API checks and quarterly audits. Process optimization targets variables with >10% objective-subjective gaps using automated profiling tools, monitored through quarterly reviews tracking metadata completion and uniqueness improvements toward >95% across dimensions.

V. Conclusion

This study evaluates Fast Payment System data quality using the QAFD framework across five dimensions. Objective results for 34 variables show high accuracy (99.99%), currency, and timeliness (100%), but lower completeness (84.41%) and uniqueness (87.34-99.96%). Subjective-objective comparison on three variables highlights gaps in completeness and uniqueness due to undocumented rules.

Recommendations: Enhance governance via metadata updates and validation. Prioritize discrepant variables in future assessments. Limitations: Limited to peak transactions on Harbolnas and six respondents. Future Directions: Extend analysis to other peak periods such as payroll dates, apply machine learning for anomaly detection, and conduct longitudinal evaluation.

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References And Footnotes

[1] BI, “Laporan Kebijakan Moneter Triwulan III 2025,” bi.go.id. Accessed: Jan. 08, 2026. [Online]. Available: https://www.bi.go.id/id/publikasi/laporan/Pages/Laporan-Kebijakan-Moneter-Triwulan-III-2025.aspx

[2] BI, “Blueprint Sistem Pembayaran Indonesia 2030,” Situs Bank Indonesia. Accessed: Sep. 17, 2024. [Online]. Available: https://www.bi.go.id/id/publikasi/kajian/Pages/Blueprint-Sistem-Pembayaran-Indonesia-2030.aspx

[3] BI, “Sistem Pembayaran & Pengelolaan Uang Rupiah,” Situs Bank Indonesia. Accessed: Sep. 17, 2024. [Online]. Available: https://www.bi.go.id/id/fungsi-utama/sistem-pembayaran/default.aspx

[4] Firstlogic, “Data Quality in the Financial Sector.” [Online]. Available: https://firstlogic.com/insights/data-quality-in-the-financial-sector

[5] DQLabs, “Financial Data Quality Management: How to Improve It.” [Online]. Available: https://www.dqlabs.ai/blog/how-to-improve-your-financial-data-quality-management/

[6] Dost, “The importance of financial data quality management | Dost.” Accessed: Jan. 08, 2026. [Online]. Available: https://www.dost.io/blog/the-importance-of-data-quality-in-finance

[7] Swift, “Payments Data Quality | Swift.” Accessed: Jan. 08, 2026. [Online]. Available: https://www.swift.com/products/payments-data-quality

[8] A. Faragallah and M. T. Chimenti, “Indonesia – Financial Sector Assessment Program : Technical Note - Assessment of the BI-SSSS Based on CPMI-IOSCO Principles for Financial Market Infrastructure,” Washington, D.C., Nov. 2024. [Online]. Available: http://documents.worldbank.org/curated/en/099110424110037314

[9] M. Alrawad, A. Lutfi, M. A. Almaiah, and I. A. Elshaer, “Examining the influence of trust and perceived risk on customers intention to use NFC mobile payment system,” *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 9, no. 2, p. 100070, Jun. 2023, doi: 10.1016/j.joitmc.2023.100070.

[10] Q. Zhang and H. Kim, “From Social to Financial: Understanding Trust in Extended Payment Services

on Social Networking Platforms," *Behavioral Sciences*, vol. 15, no. 5, p. 659, May 2025, doi: 10.3390/bs15050659.

[11] I. H.-Y. Chiu, "A new era in fintech payment innovations? A perspective from the institutions and regulation of payment systems," *Law Innov. Technol.*, vol. 9, no. 2, pp. 190–234, Jul. 2017, doi: 10.1080/17579961.2017.1377912.

[12] Pasardana.id, "Bank Indonesia Hadirkan Statistik Sistem Pembayaran Infrastruktur." Accessed: Jan. 08, 2026. [Online]. Available: https://pasardana.id/news/2021/7/30/bank-indonesia-hadirkan-statistik-sistem-pembayaran-infrastruktur/

[13] BI, "Statistik Sistem Pembayaran dan Infrastruktur Pasar Keuangan (SPIP)," Situs Bank Indonesia. Accessed: Sep. 17, 2024. [Online]. Available: https://www.bi.go.id/id/statistik/ekonomi-keuangan/spip/Default.aspx

[14] BIS, "About the payments and financial market infrastructures statistics." [Online]. Available: https://www.bis.org/statistics/dataportal/payment_stats.htm?m=6%7C36

[15] W. Badrawani, C. Amanda, N. Maryaningsih, A. Ginulur, and C. S. Wulandari, "Transaksi Digital Dan Pertumbuhan Ekonomi: Velositas Uang Menggunakan Data Sistem Pembayaran," Bank Indonesia, 2024. doi: None.

[16] F. Peranginangin, "Payment System Statistics to Support Policy Formulation in Indonesia," in *Proceedings of The ISI Regional Statistics Conference 2017 (ISI RSC 2017)*, Bali, 2017, pp. 547–553. [Online]. Available: https://isi-web.org/sites/default/files/2025-04/Proceeding-International-Statistic-Institute.pdf

[17] M. Hellqvist and K. T. T.-I. payments as a new normal: C. study of liquidity impacts for the F. market Korpinen, "Instant payments as a new normal: Case study of liquidity impacts for the Finnish market," Bank of Finland, 2021. doi: None.

[18] Xendit, "Optimizing Harbolnas: The Strategic Role of Payment Gateways." Accessed: Jan. 17, 2026. [Online]. Available: https://www.xendit.co/en-id/blog/optimizing-harbolnas-the-strategic-role-of-payment-gateways-in-conversion-security-and-business-stability/

[19] M. Bendechache, J. Attard, M. Ebiele, and R. Brennan, "A Systematic Survey of Data Value: Models, Metrics, Applications and Research Challenges," *IEEE Access*, vol. 11, pp. 104966–104983, 2023, doi: 10.1109/ACCESS.2023.3315588.

[20] F. de Amicis and C. Batini, "A methodology for data quality assessment on financial data," *Studies in communication sciences : journal of the Swiss Association of Communication and Media Research*, vol. 4, no. 2, p. 115, 2004, doi: 10.5169/seals-790977.

[21] H. D. Sitawati, Y. Ruldeviyani, A. N. Hidayanto, R. C. Amanda, and A. S. Nugroho, "Data Quality Improvement: Case Study Financial Regulatory Authority Reporting," *2021 International Seminar on Machine Learning, Optimization, and Data Science, ISMODE 2021*, pp. 272–277, 2022, doi: 10.1109/ISMODE53584.2022.9743087.

[22] C. Cichy and S. Rass, "An overview of data quality frameworks," *IEEE Access*, vol. 7, pp. 24634–24648, 2019, doi: 10.1109/ACCESS.2019.2899751.

[23] DAMA International, *DAMA-DMBOK: Data Management Body of Knowledge (2nd Edition)*. Denville, NJ, USA: Technics Publications, LLC, 2017.

[24] R. Miller, H. Whelan, M. Chrubasik, D. Whittaker, P. Duncan, and J. Gregório, "A Framework for Current and New Data Quality Dimensions: An Overview," *Data (Basel).*, vol. 9, no. 12, p. 151, Dec. 2024, doi: 10.3390/data9120151.

[25] M. del P. Angeles and F. García-Ugalde, "A Data Quality Practical Approach," *International Journal on Advances in Software*, vol. 2, no. 2 & 3, pp. 259–274, 2009, [Online]. Available: http://www.iariajournals.org/software/

[26] N. Blomqvist, "Data quality methodologies and improvement in a data warehousing environment with financial data," Lappeenranta University of Technology, 2019.

[27] R. Miller, S. H. M. Chan, H. Whelan, and J. Gregório, "A Comparison of Data Quality Frameworks: A Review," *Big Data and Cognitive Computing*, vol. 9, no. 4, p. 93, Apr. 2025, doi: 10.3390/bdcc9040093.

[28] Z. Majkić, "A general framework for query answering in data quality-based Cooperative Information Systems," in *Proceedings of the ACM SIGMOD International Conference on Management of Data*, 2004, pp. 44–50. doi: 10.1145/1012453.1012461.

[29] M. Scannapieco, A. Virgillito, C. Marchetti, M. Mecella, and R. Baldoni, "The DaQuinCIS architecture: a platform for exchanging and improving data quality in cooperative information systems," *Inf. Syst.*, vol. 29, no. 7, pp. 551–582, Oct. 2004, doi: 10.1016/j.is.2003.12.004.

[30] M. A. Jeusfeld, C. Quix, and M. Jarke, "Design and Analysis of Quality Information for Data Warehouses," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 1507, no. 1, 1998, pp. 349–362. doi: 10.1007/978-3-540-49524-6_28.

[31] M. Helfert and C. Herrmann, "Proactive Data Quality Management for Data Warehouse Systems - A Metadata based Data Quality System," 2002. [Online]. Available: https://www.alexandria.unisg.ch/handle/20.500.14171/71891

[32] C. S. Carson, "Toward a framework for assessing data quality," p. 69 p. :, 2001, [Online]. Available: http://digitallibrary.un.org/record/440024

[33] IMF, "Data Quality Assessment Framework and Data Quality Program," Fifth Review of the Fund's Data Standards Initiatives. Accessed: Jan. 18, 2026. [Online]. Available: https://www.imf.org/external/np/sta/dsbb/2003/eng/dqaf.htm

[34] BIS, "Principles for effective risk data aggregation and risk reporting," no. January 2013, p. 28, 2013, [Online]. Available: http://www.bis.org/publ/bcbs239.pdf

[35] H. Harreis, T. Ho, J. Machado, P. Merrath, K. Rowshankish, and A. Tavakoli, "Living with BCBS 239," 2017. [Online]. Available: http://dln.jaipuria.ac.in:8080/jspui/bitstream/123456789/6694/1/Living-with-BCBS-239.pdf

[36] J. Orgeldinger, "The Implementation of Basel Committee BCBS 239: Short analysis of the new rules for Data Management," *Journal of Central Banking Theory and Practice*, vol. 7, no. 3, pp. 57–72, Sep. 2018, doi: 10.2478/jcbtp-2018-0023.

[37] D. Y. Siregar, H. Akbar, I. B. P. A. Pranidhana, A. N. Hidayanto, and Y. Ruldeviyani, "The Importance of Data Quality to Reinforce COVID-19 Vaccination Scheduling System: Study Case of Jakarta, Indonesia," *Proceedings - 2022 2nd International Conference on Information Technology and Education, ICIT and E 2022*, pp. 262–268, 2022, doi: 10.1109/ICITE54466.2022.9759880.

[38] W. A. Bowo, A. Suhanto, M. Naisuty, S. Ma'mun, A. N. Hidayanto, and I. C. Habsari, "Data Quality Assessment: A

Case Study of PT JAS Using TDQM Framework," in *2019 Fourth International Conference on Informatics and Computing (ICIC)*, IEEE, Oct. 2019, pp. 1–6. doi: 10.1109/ICIC47613.2019.8985896.