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Evaluation of Electronic Health Record Data Quality: A Case Study of a Government General Hospital in Jakarta

Iindra Iriyanti*, Isnina Eva Hidayati, Nur Indrawati, Dana Indra Sensuse
Universitas Indonesia, Indonesia
Email: iindra.iriyanti@ui.ac.id*, isnina.eva@ui.ac.id, nur.indrawati21@ui.ac.id, dana@cs.ui.ac.id

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ABSTRACT
The digital transformation of healthcare is a global priority for improving service efficiency, information system integration, and data-driven decision-making. In Indonesia, government hospitals are pioneering the implementation of digital transformation policies through the SATUSEHAT program, which aligns with the Health Level Seven International (HL7) initiative to implement global health data interoperability standards. This program requires the hourly submission of Electronic Health Record (EHR) data to the Ministry of Health of the Republic of Indonesia's SATUSEHAT platform, with the requirement that the data meet the dimensions of completeness, accuracy, timeliness, and consistency. This study aims to evaluate the quality of EHR data at a central government general hospital in Jakarta using the Total Data Quality Management (TDQM) framework and linking it to the principles of HL7 Fast Healthcare Interoperability Resources (FHIR). This study involved in-depth interviews with the EHR development team and a quantitative analysis of data from the hospital's Health Information System (HIS) and data warehouse for outpatients during the period of December 1–31, 2025. The results showed that the quality of EHR data did not fully meet the four main dimensions of data quality. A total of 13.16% of EHR data was rejected by the SATUSEHAT platform. Key recommendations include synchronizing population data with the Directorate General of Population and Civil Registration and improving data quality governance capabilities within government hospitals. This research provides a strategic contribution to national efforts to build an integrated, interoperable, and globally standardized digital health system.

INTRODUCTION

The development of information and communication technology has changed the paradigm of health service delivery throughout the world (World Health Organization [WHO], 2021). Digital transformation in the health sector is now a global strategic agenda initiated by the World Health Organization (WHO) through the Global Strategy on Digital Health 2020–2025. This strategic agenda emphasizes the importance of utilizing digital technology to strengthen health systems, increase service efficiency, and support data-driven policies (WHO, 2021). The implementation of Electronic Health Records (EHR) is a fundamental foundation for the digitalization of healthcare services because it enables the integration of patient data in real time across healthcare facilities (WHO, 2021).

To ensure that medical data exchange can be conducted securely and in a standardized manner, the WHO and Health Level Seven International (HL7) developed the Fast Healthcare Interoperability Resources (FHIR) standard, which is now a global reference for digital health interoperability systems, particularly in WHO member states (WHO, 2021). Indonesia, as a WHO member state, participates in implementing international standards for digital health transformation and EHR adoption. EHR implementation has become a national health policy. Through Minister of Health Regulation No. 24 of 2022 concerning Electronic Medical Records, the government has mandated the implementation of EHR in all healthcare facilities. Hospitals are one such facility in Indonesia and serve not only as healthcare service providers but also as implementation centers for national health policies, including EHR adoption (Kementerian Kesehatan, 2025). The Central Government General Hospital in Jakarta (XYZ Hospital) is a healthcare facility provider (Bhavnani & Berlianto, 2022; Panudju, n.d.; Setiawan & Wijayati, 2024).

Therefore, XYZ Hospital has also participated in implementing EHR in the patient care process. Based on internal data, XYZ Hospital handled 106,200 outpatient visits with a total of 53,272 patients in December 2025. With such a high volume of services, it is important for XYZ Hospital to consistently maintain high EHR data quality (Beauvais et al., 2021; Förstel et al., 2024). The implementation of EHR at XYZ Hospital is carried out comprehensively, covering patient admission, discharge, referral, and death. EHR at XYZ Hospital serves as the basis for processing information for reporting purposes, such as patient and disease statistics, as well as supporting analytical functions to predict disease trends in a region (Almansouri et al., 2024; Dong et al., 2025; HL et al., 2023).

Initially, medical records were used only as documentation of patients' medical history, diagnoses, and treatment records (Lewis et al., 2023). However, with the implementation of Electronic Health Records (EHR), medical records now serve not only as documentation tools but also support clinical analysis, research, and decision-making processes (Lewis et al., 2023). Given the expanded functions of EHR, data quality must be ensured at a high standard. Good EHR data quality is highly dependent on accurate and timely data entry during service delivery (Lewis et al., 2023). If data quality is poor, managerial decisions may become misaligned with intended outcomes (Lewis et al., 2023). Furthermore, based on Minister of Health Regulation (PMK) No. 24 of 2022 concerning Medical Records and PMK No. 18 of 2022 concerning the Implementation of One Health Sector Data through the Health Information System, the SATUSEHAT platform is designated as an integrated system for collecting, managing, and sharing individual health data across healthcare facilities (fasyankes) in Indonesia. SATUSEHAT enables digital integration of patient medical records, identity verification, and health claims submission, thereby simplifying administration and accelerating patient services (Kementerian Kesehatan, 2022).

To standardize EHR data quality across healthcare facilities in Indonesia, the Ministry of Health (Kemenkes) has issued implementation guidelines for data submission to the SATUSEHAT platform (Kementerian Kesehatan, 2022). These guidelines define detailed variables for each service unit, including the Emergency Department (IGD), Outpatient, Inpatient, Laboratory, and Pharmacy units (Evryna, 2026; Rabbani et al., 2018; Yiadom et al., 2020). XYZ Hospital began integrating its services with the SATUSEHAT platform on December 22, 2022, as part of a national digital system to improve access and efficiency of

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healthcare services in Indonesia. Since implementation, it was found that some patients' Population Identification Numbers (NIK) were rejected by the SATUSEHAT system because the data could not be matched in its database. This reflects challenges in cross-system data synchronization, which remains a key issue in health digitalization (Le, 2026; Selvam, 2026).

It is expected that all EHR data from XYZ Hospital can be transmitted to SATUSEHAT in real time and meet the data quality requirements established by the Ministry of Health in terms of completeness, accuracy, timeliness, and consistency. In this regard, this study is necessary to measure the quality of EHR data at XYZ Hospital in accordance with national medical record standards and the SATUSEHAT platform requirements, and to ensure full system acceptance. Data quality measurement is essential because EHR data are susceptible to quality issues (Ozonze et al., 2023). Selecting appropriate tools to monitor and evaluate data quality improvement efforts remains a significant challenge (Lewis et al., 2023).

In this study, the author uses the Total Data Quality Management (TDQM) framework to measure EHR data quality at XYZ Hospital, providing a structured approach to improving data quality management (Ozonze et al., 2023). The methods used include both quantitative and qualitative approaches. The quantitative method involves measuring data quality using SQL-based data extraction, while the qualitative method involves interviews with data engineers and analysts to interpret the results and develop recommendations. Data quality assessment is conducted following the TDQM stages and referring to standards established by the Ministry of Health.

The urgency of this study is driven by the critical need for reliable data to support the government's digital health transformation strategy. The SATUSEHAT initiative is a cornerstone of Indonesia's healthcare digitalization, aiming to establish a unified and interoperable national health data system. Data quality issues at the hospital level may undermine this national effort. As a primary data source for the national platform, the accuracy and completeness of XYZ Hospital's EHR are not only a local concern but also a national imperative. This research is therefore essential to support the success of the SATUSEHAT program and the broader objectives of digital health transformation in Indonesia.

Based on a literature review, previous studies on EHR data quality have generally focused on dimensions such as completeness, consistency, and timeliness (Lewis et al., 2023). However, no study has specifically evaluated EHR data quality based on the four dimensions established by the Indonesian Ministry of Health (Kementerian Kesehatan, 2022), nor has it applied the TDQM framework in the context of a national government hospital such as XYZ Hospital. Therefore, this study addresses this gap by evaluating EHR data quality using TDQM, thereby contributing empirical evidence to the implementation of data quality management in Indonesia's public health sector.

METHOD

. This study adopted a mixed-methods approach, combining qualitative methods and a systematic literature review (SLR) to identify data quality dimensions and interoperability principles used as indicators for assessing EHR data quality. Based on the identified indicators, quantitative methods were applied to measure data quality, while qualitative methods in the form of interviews were used to interpret the results and explain observed data quality issues.

The quantitative analysis was conducted by querying the SIMRS database stored in MySQL and the data warehouse (DWH) stored in MariaDB. The system transmitted data to

SATUSEHAT on an hourly basis. The data analyzed included patient demographic and visit data for December 2025.

The qualitative component involved interviews with data engineers and data analysts at XYZ Hospital to interpret the results of the data quality assessment and to identify recommendations for addressing the issues found.

The literature review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) 2020 guidelines (Page et al., 2021) to ensure systematic identification and selection of relevant studies. The Boolean search string used was:

(("Electronic Health Record" OR "EHR") AND "data quality" OR "Total Data Quality Management" OR "SATUSEHAT")

The search was conducted across five databases: Scopus, SpringerLink, IEEE Xplore, ProQuest, and ScienceDirect, using predefined inclusion and exclusion criteria as presented in Table II. The study selection process is summarized in Figure 1.

Table 1. SLR Inclusion, Exclusion

Mechanism	Description
Inclusion	Articles published between 2020-2025, articles written in English, article type "conference" OR "journal", article subject area is "computer science" OR "Information technology", articles focus on data quality assessment in Electronic Health Record with TDQM or SATUSEHAT issues.
Exclusion	Written in non-English, the paper cannot be accessed, duplicated paper and the abstract is not about EHR or quality data assessment

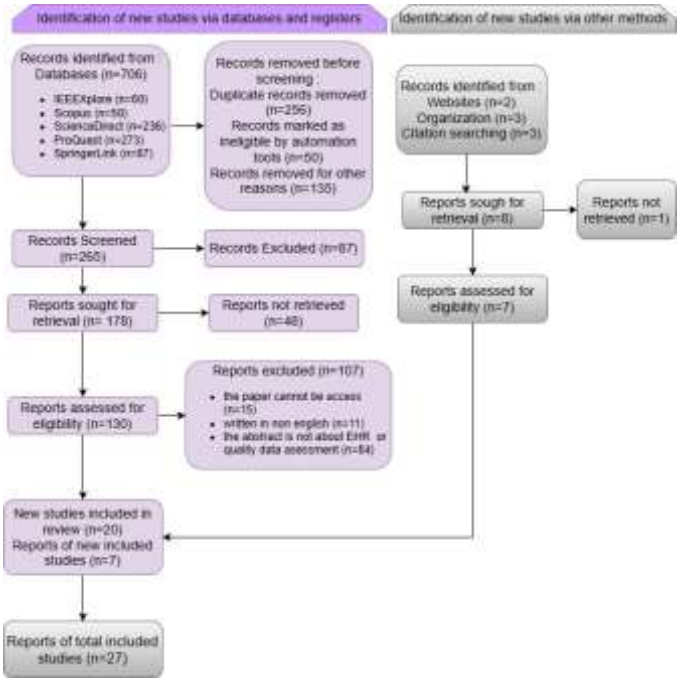

Figure 1. SLR PRISMA 2020 Flow Diagram

From the SLR search results with PRISMA 2020, we obtained 27 papers, consisting of 20 papers discussing data quality assessment, specifically in the healthcare and EHR sectors, using both the TDQM framework and other frameworks that focus on data quality, data accuracy, and how to achieve them. In addition, there are three papers on the Ministry of Health

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regulations related to EHR and SATUDATA Indonesia, as a reference for regulations applicable in Indonesia. As an additional reference, we found two papers on HL7 to gain insight into global health data interoperability standards. Meanwhile, we used additional references from the DMBOK on data quality management.

In addition to SLR, this research follows the 3 initial cycles of TQM, namely define, measure and analyze (DMA), as follows:

1. Define, at this stage, the things that are done are as follows:
   - Stage 1: Identification of data to be measured based on the provisions, for XYZ Hospital EHR data, the data to be measured is data in the patient identity table and data in the patient visit table.
   - Stage 2: Determine the dimensions of data quality based on the Regulation of the Minister of Health of the Republic of Indonesia Number 18 of 2022 concerning the Implementation of Data for One Health Sector Through the Health Information System, namely completeness, accuracy, timeliness and consistency.
   - Stage 3: Define business rules for each criterion to detect data anomalies. There are 20 business rules for data completeness, 14 for accuracy, 1 for timeliness, and 10 for data consistency.
2. Measure, at this stage data quality measurements are carried out.
   - Stage 4: Data collection by conducting direct queries into the SIMRS system using business rules established in the design stage. Queries are conducted into the SIMRS and DWH databases for XYZ Hospital EHR data for the period 1 to 31 December 2025. The query results will be compared with the established business rules.
   - Stage 5: Measuring data quality based on predetermined criteria. The result of this data quality measurement is the percentage of data conformance to the rules in the RME data.
3. Analyze, at this stage the results of data quality measurements are analyzed.
   - Stage 6: Analysis of the causes of anomalies in the data and recommendations for resolution were carried out by conducting interviews with the XYZ Hospital EHR Team.
   - Stage 7: Provide conclusions and recommendations based on the results of data quality measurements in the previous stage.
4. Improve, at this stage it is expected that XYZ HOSPITAL can carry out the recommendations presented in this study so that they are not included in the scope of the study.

RESULT AND DISCUSSION

Data quality measurement is carried out using the TDQM framework. EHR data is measured based on the Regulation of the Minister of Health of the Republic of Indonesia Number 18 of 2022, Article 7, paragraph (4), where quality health data includes 4 (four) dimensions, namely data completeness, data accuracy, timeliness, and data consistency (Kementerian Kesehatan, 2022) and data completeness measurements based on SATUSEHAT's requests. Measurements were conducted by evaluating whether the data in the

system complies with the business rules defined for each data quality dimension. Data verification was performed by comparing records in the data warehouse (DWH) with those in the hospital information system (SIMRS). The DWH contains data that have been successfully transmitted to the SATUSEHAT platform, while the SIMRS represents the complete set of hospital data at RS XYZ.

The data quality measured is the mandatory data requested by SATUSEHAT: patient identity data with 15 columns and visit data with 5 columns, resulting in a total of 20 columns measured. The data used in this study is outpatient visit data at XYZ Hospital in December 2025. Outpatients visit patient data in December 2025 amounted to 106,200 outpatient visits with a total of 53,272 patients.

The measurement results display the percentage of data conformity for each dimension, as shown in Table III. The table shows that of the 20 business rules in the data completeness dimension, only 8 or 40% meet the requirements (100% complete), 9 business rules (45%) do not meet the completeness criteria, and 3 business rules cannot be measured for their data completeness. Meanwhile, for the data accuracy dimension, none of the 8 business rules (57%) meet the accuracy criteria, and the remaining 6 business rules cannot be measured. The same thing also occurs in the timeliness and data consistency dimensions, where no business rules meet the requirements related to timeliness and consistency.

Table 2. Data quality measurement results

Dimensions	Number of Business Rules	Fulfilled		Not Fulfilled		Unmeasurable	
	Total	Total	Percentage	Total	Percentage	Total	Percentage
Completeness	20	8	40	9	45	3	15
Accuracy	14	0	0	8	57	6	43
Timeliness	1	0	0	1	100	0	0
Consistency	10	0	0	10	100	0	0

Data Completeness Measurement

The completeness dimension in this study aims to identify anomalous data in the form of attributes expected in the XYZ Hospital EHR that must be sent to SATUSEHAT. These attributes are divided into general patient identity data, newborn identity data, and visit data. The patient identity attributes used in this study consist of:

1. C1 Patient's SATUSEHAT number
2. C2 Full name
3. C3 National Identification Number (NIK)
4. C4 Passport/KITAS (foreign nationals only)
5. C5 Place of birth
6. C6 Date of birth
7. C7 Gender
8. C8 Guarantor's name
9. C9 Guarantor's telephone number
10. C10 Baby names
11. C11 Mother's National Identification Number

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12. C12 Medical record number
13. C13 Baby's date of birth
14. C14 Time of birth
15. C15 Multiple births
16. Visit data attributes consist of:
17. C16 Visit number
18. C17 Visit status
19. C18 Type of visit
20. C19 Room/polyclinic
21. C20 Class

The business rules for the 20 attributes are said to be incomplete if there is empty data or it contains unknown, N/A, spaces or null.

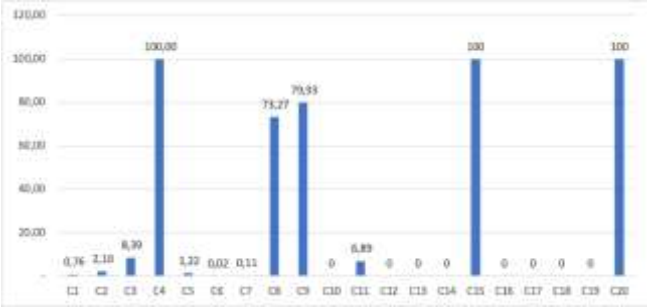

Figure 2. Data Completeness Assessment in XYZ Hospital's HER

Based on Figure 2, it can be concluded that of the 20 patient and visit data columns, 12 columns still have unfilled data. Three of these columns are data that cannot be measured: passport/KITAS, multiple births, and class. This does not meet the expectations for data delivery to SATUSEHAT, where mandatory data, especially the NIK, must be filled in completely.

The remaining unfilled patient SATUSEHAT number and NIK indicate that not all patient data at XYZ HOSPITAL can be sent 100% to the SATUSEHAT platform. This incompleteness affects patient data rejection, so patients visiting the hospital cannot access their medical records on SATUSEHAT mobile. Details of the query results for measuring data completeness and details for 20 attributes can be seen in attachments 1 and 2.

Data Accuracy Measurement

The accuracy measurement dimension of this study is to assess the accuracy of XYZ Hospital's data compared to data from trusted sources. The data measured for accuracy are Patient Identity Data, which serves as initial validation on the SATUSEHAT platform, and Visit Data. The rules used to measure data accuracy include:

1. A1 IDSATUSEHAT number according to the Ministry of Health format
2. A2 NIK number is not rejected by SATUSEHAT
3. A3 16-digit NIK format
4. A4 Date of birth according to the rules on the NIK
5. A5 Gender according to the rules in the NIK
6. A6 Gender must be F or M
7. A7 Birth time according to actual birth time

8. A8 Guarantor's Telephone Number contains numbers if the guarantor's name is filled in

The results of the data quality measurements can be seen in Figure 3, as follows:

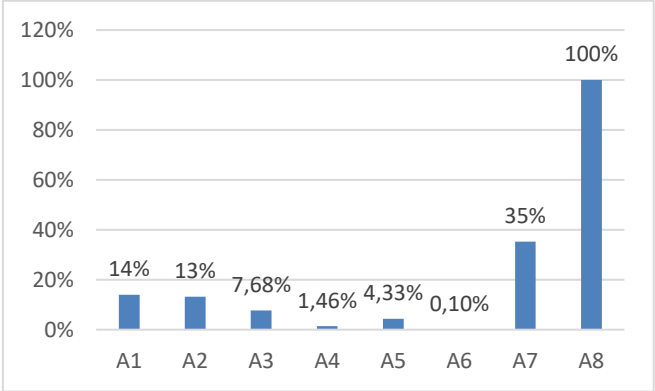

Figure 3. Data Accuracy Assessment in XYZ Hospital's HER

The accuracy measurements for the eight business rules that met the overall requirements were inaccurate. Furthermore, six business rules could not be measured for accuracy, namely:

1. A9 Full name and place of birth need to be synchronized with Dukcapil for accuracy.
2. A10 Passport/KITAS and Medical Record Number do not have a specific format so their accuracy cannot be measured.
3. A11 Guarantor Name, Visit Number and Room/Polyclinic can be filled in freetext by the user according to the information obtained.
4. A12 Visit Status and Visit Type are automatically filled in as Outpatient
5. A13 Multiple births: not recorded and sent to SATUSEHAT
6. A14 Class, cannot be measured because there are no classes for outpatients.

Details of the query results for accuracy measurements and their details for 14 attributes can be seen in appendix 1 and appendix 2.

Timeliness Measurement

The timeliness measurement dimension of this study is the extent to which EHR data at XYZ Hospital is sent on time to the SATUSEHAT platform. Based on the query results, 5,449 or approximately 13.16% of patient data were not updated to the SATUSEHAT platform because the NIK was incorrect, thus concluding that the data was not sent on time. Details of the query for the results of the timeliness measurement and its details can be seen in attachments 1 and 2.

Data Consistency Measurement

The data consistency measurement dimension of this study is to measure how consistent XYZ Hospital's data is by comparing the data types in the data warehouse ready to be sent to SATU SEHAT and the data types in the SIMRS database. In this study, it is expected that the data types in the data warehouse will be the same as those in the SIMRS database. To measure data consistency, researchers sampled the table structures in the patient identity column and the visit table structure in the data warehouse with those in the SIMRS database. Consistency was measured by setting a threshold for the extent of possible differences between the two data sets.

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Table 2. Assessment of patient data tables and patient visits based on data consistency dimensions

Column Name (DWH)	Column Name (SIMRS)	Data Type (DWH)	Data Type (SIMRS)	Explanation
PatientID	person_id	bigint	int(10) unsigned	Differences in data type sizes.
PatientName	person_nm	varchar(255)	text	Difference between data types (varchar vs text)
BirthDate	birth_dttm	datetime2(0)	text	Undefined date format in SIMRS
Gender	adm_gender_cd	char(1)	enum('m','f','u')	DWH uses char, SIMRS enum
Address	addr_txt	varchar(255)	text	Differences in data types
PostalCode	zip_cd	char(5)	varchar(5)	Difference between data types (char vs varchar)
ReligionID	religion_cd	smallint	smallint(5) unsigned	Same type, but different length
BloodType	blood_t	varchar(2)	enum('A','B','0','AB',...)	Differences in data representation approaches
Education	education	varchar(100)	tinyint(3) unsigned	Different approaches to educational values
Race	race_nm	varchar(255)	char(255)	Difference between data types (varchar vs char)

Table 3 shows the consistency of data types and column names 100% not the same between the SIMRS and DWH databases of XYZ Hospital. Details of the query results of data consistency measurements and their details can be seen in appendix 1 and appendix 2. Based on the results obtained in each dimension for data quality at XYZ Hospital, several causes of the problem were found. The analysis was carried out through observation and interviews with SATUSEHAT data management staff.

Analysis of EHR Data measurement results based in interviews

The interviewees for this study were selected purposively based on their roles in EHR. Helathcare team, the data warehouse team, and IT personnel were selected because they are directly involved in the process of inputting, validating, mapping, and submitting data to the SATUSEHAT platform. Therefore, their insights are highly relevant for evaluating the quality of the data generated and understanding operational challenges encountered in practice. Measuring EHR quality is clinical and menagerial decision-making, inaccurate or incomplete data can lead to the risk of misdiagnosis, delays in care, and inaccurate reporting to regulators.

Interviews were conducted to explore the underlying causes of the quantitative findings and identify technical and organizational factors that caould not be identified through data analysis alone. One key finding was that EHR data could not be fully transmitted to SATUSEHAT due to differences in variable structure, format, and standard terminology between the hospital's EHR system and the data warehouse used as the integration source. A source from the data warehouse team stated: "The data in the warehouse is not yet fully aligned with SATUSEHAT's data structure. Some mandatory variables, such as service codes, are not fully available in our system, so they cannot be fully transmitted". This finding was reinforced

by statements from medical records staff who said: “There are often mismatches between the data recorded in the EHR and the data required by SATUSEHAT. Sometimes the formats are different, sometimes the data is empty, so the transmission process is hampered.” The IT staff also added: “Automatic integration is actually possible, but the infrastructure and data standardization must be improved first. As long as there is no uniformity, there will definitely be data that fails to be transmitted."

EHR data must good quality, accurate, complete, and consistent becouse the entire medical service process from history taking and diagnosis on its reliability. Furthermore, national standards such as SATUSEHAT require hospitals to provide valid data to support interoperability between helathcare facilities. Therefore, this qualitative analysis provides an in-depth understanding of the technical and organizational reasons behind suboptimal EHR data quality and demonstrates why improving data quality is a crucial part of the digital transformation of government hospitals.

Based on the research results above, we found some of the problems that occur are as follows:

1. There is no synchronization of XYZ Hospital data with DUKCAPIL, so that there is NIK data that is rejected by SATUSEHAT and/or BPJS.
2. Unavailability of columns requested by SATUSEHAT in the data sent by XYZ Hospital such as multiple births and class.
3. There are data formats inputted in SIMRS that do not comply with the provisions, for example: there are still NIK formats that are not 16 digits.
4. There is NIK data that does not comply with the format set by DUKCAPIL regarding the NIK format for date of birth and gender.
5. There is gender data that is not filled in with the correct format (F or M).
6. There is a data column that is not sent to SATUSEHAT, namely "Multiple Births".
7. There is a “Type of Visit” column that is not in SIMRS but needs to be sent to SATUSEHAT so that it is automatically filled in with “Outpatient”.
8. The NIK and biological mother's NIK columns are still combined into one.
9. The data type in the SIMRS table is not the same as the data warehouse table that is ready to be sent to SATUSEHAT.

Strategic recommendations that can be implemented at XYZ Hospital include data quality management to ensure that the data generated by the EHR supports effective and efficient services, as follows:

1. Proposing the synchronization of SIMRS data with the Ministry of Home Affairs, in this case the Directorate General of Population and Civil Registration (DUKCAPIL), so that during the registration process, validation regarding NIK has been carried out so that the data sent to SATUSEHAT is 100% acceptable and the NIK data in SIMRS is accurate.
2. Creating a Standard Operating Procedure (SOP) as a binding provision so that users input data according to the provisions and adding validation to columns that require special formats such as NIK and gender to comply with business rules.
3. Provide training to users so that they can fill in data accurately, for example, the baby's birth time must match the actual data.
4. Building a data dictionary that establishes the rules required to meet the dimensions of data quality in terms of completeness, accuracy, timeliness, and consistency in accordance with

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the provisions of the Ministry of Health which refer to the provisions of HL7 and are adapted to the data and information needs in Indonesia.

CONCLUSION

The results of the data quality measurement at XYZ Hospital showed that, in the completeness dimension, 8 out of 20 business rules (40%) achieved 100% completeness. In the accuracy dimension, 8 out of 14 business rules (57%) were identified as inaccurate, while the remaining 6 rules could not be evaluated due to data limitations. In the timeliness dimension, XYZ Hospital was unable to transmit patient data to the SATUSEHAT platform in a timely manner, as 5,449 records, or approximately 13.16% of patient data, had not been updated to the platform. In the consistency dimension, discrepancies were identified between data types in the SIMRS database and those in the data warehouse.

Several data quality issues were identified, including missing values in multiple EHR tables at XYZ Hospital, absent required data fields, invalid data entries, delayed data transmission to SATUSEHAT, and inaccuracies in patient identity information. This study provides value for XYZ Hospital in assessing the current quality of its EHR data. By understanding existing conditions, the hospital can implement targeted improvements to enhance data quality and optimize its use, particularly for users of the SATUSEHAT mobile platform.

A limitation of this study was that the data used for measurement were restricted to a sample of outpatient EHR records from December 2025 due to limited access permissions from the hospital. Another limitation was that only two data entities submitted to the SATUSEHAT platform were analyzed, namely patient data and visit data. Therefore, the findings may not be generalizable to other time periods, healthcare service units, or data entities within the platform.

This study applied data quality measurement based on the dimensions established by the Ministry of Health, which enables its use as a reference for future research assessing EHR data quality in other hospitals in Indonesia and evaluating data submitted to the SATUSEHAT platform. Future research is recommended to expand the scope by involving multiple hospitals and longer observation periods, as well as incorporating additional data entities such as clinical observations, diagnoses, and medication records to provide a more comprehensive assessment of data quality and interoperability at the national level.

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