Electronic Medical Records Data Quality Analysis in Supporting Smart Healthy City: A Case Study Primary Care Clinic

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ABSTRACT

The quality of Electronic Medical Records (EMR) data is a critical foundation for digital health services and Smart Healthy City implementation. Poor data quality ncluding incompleteness, inaccuracy, and lack of integration can undermine healthcare decision-making and obstruct the development of a data-driven urban health ecosystem. This study aimed to comprehensively analyze the quality of EMR data across six dimensions completeness, accuracy, consistency, timeliness, security, and integration and to assess its role in supporting Smart Healthy City implementation at Primary Care Clinic. A mixed-methods sequential explanatory design was employed. Quantitative data were collected through document audit of 150 EMR records using a structured checklist, while qualitative data were gathered through in-depth interviews with three key informants (clinic head and two healthcare staff) and document review. Results: EMR data quality demonstrated overall strong performance: timeliness reached 100%, security 91.2%, accuracy 91.1%, consistency 90.0%, completeness 87.0%, and data integration 85.7%. The overall average across all dimensions was 90.8%. Key enabling factors included management commitment (93.3%) and IT infrastructure (86.7%), while high staff workload (66.7%) and network disruptions (55.6%) were the main inhibiting factors. The EMR system demonstrated meaningful support for Smart Healthy City (85.9%), though external interoperability (73.3%) and contribution to integrated city health platforms (76.7%) remained below optimal levels. EMR data quality at Clinic is categorized as good, with timeliness as the outstanding dimension. Priority areas for improvement include strengthening end-to-end encryption, expanding interoperability using HL7-FHIR standards, and integrating the clinic's EMR with regional smart health platforms to advance the Smart Healthy City agenda.

Keywords : Data Quality; Digital Health; Electronic Medical Records; Primary Care; Smart Healthy City

INTRODUCTION

The digital transformation of healthcare has accelerated the adoption of Electronic Medical Records (EMR) in primary care settings worldwide. EMR systems serve as the backbone of health information management, enabling efficient data storage, retrieval, and exchange across care settings (1). In Indonesia, the Ministry of Health has mandated EMR implementation across all healthcare facilities, reinforcing its role in national health data governance through the SATUSEHAT platform (2). Beyond administrative utility, EMR data has become the primary resource for evidence-based policy-making, epidemiological surveillance, and the development of integrated digital health ecosystems (3).

The Smart Healthy City concept integrates smart city principles with health oriented urban governance, leveraging technology to create responsive, data-driven, and citizen centered health services(4)(5). Central to this vision is the availability of high-quality health data that enables monitoring of population health status, early disease detection, inter-facility care coordination, and data-driven policy formulation . Electronic medical records, as the primary source of clinical data at the point of care, serve as the foundational input for such integrated health ecosystems.

However, the quality of EMR data in primary care settings particularly in developing countries remains a significant challenge(6). Studies consistently report issues such as incomplete documentation, inaccurate diagnosis coding, data inconsistencies across visits, delayed data entry, weak security protocols, and limited interoperability (7)(8)(9).These quality deficiencies directly compromise the reliability of health information systems and reduce the effectiveness of digital health interventions (10)(11).

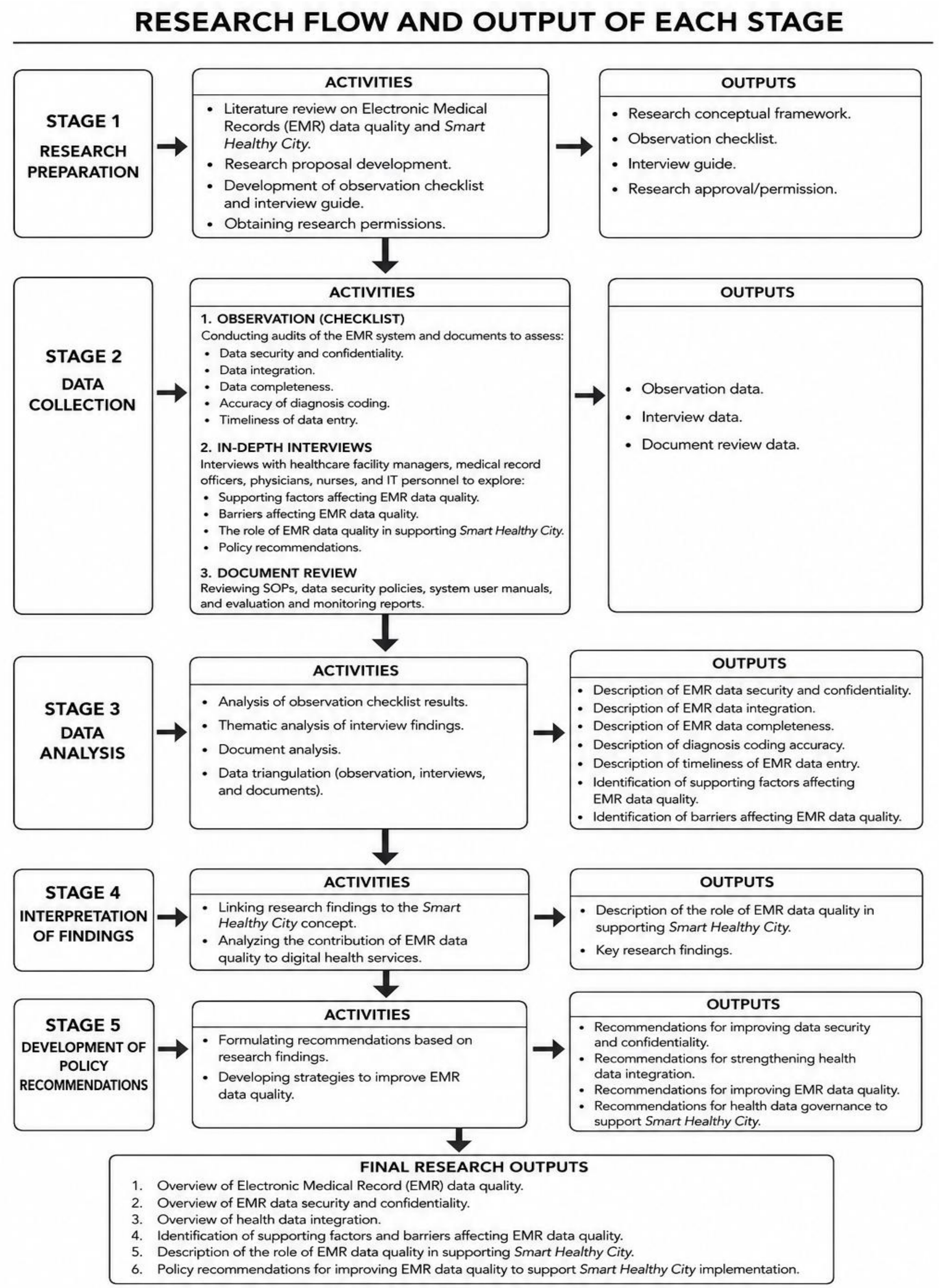
Previous research has predominantly examined EMR quality from administrative or clinical perspectives, focusing on completeness and coding accuracy in hospital settings(12)(13). Studies linking EMR data quality to Smart Healthy City implementation at the primary care level are notably scarce, despite the critical role that primary care clinics play as the first point of contact in community health systems. This research gap is particularly significant in Indonesia, where the transition from paper-based to electronic health records is still ongoing at the primary care level.

The novelty of this study lies in its comprehensive, multi-dimensional analysis of EMR data quality using Wang and Strong's (1996) data quality framework, applied specifically within the Smart Healthy City context. Unlike prior studies that treat EMR quality as an administrative metric, this research positions EMR data quality as a strategic asset for urban health governance and digital health development. The study was conducted at Dr. Sriningsih Primary Care Clinic, a FKTP (Fasilitas Kesehatan Tingkat Pertama) that has implemented an EMR system and represents a typical primary care setting in Indonesian mid-sized cities.

This study aimed to: (1) analyze EMR data completeness; (2) assess EMR data accuracy; (3) evaluate EMR data consistency; (4) examine timeliness of EMR data entry; (5) assess the security and confidentiality of EMR data; (6) analyze EMR data integration in supporting digital health services; (7) identify enabling and inhibiting factors for EMR data quality; (8) analyze the role of EMR data quality in supporting Smart Healthy City implementation; and (9) formulate strategic recommendations for improving EMR data quality toward Smart Healthy City development.

METHODS

This study employed a mixed-methods sequential explanatory design, conducted in two sequential phases. In the first (quantitative) phase, an EMR document audit was performed to objectively measure data quality across six dimensions: completeness, accuracy, consistency, timeliness, security, and integration. In the second (qualitative) phase, in-depth interviews and document review were conducted to explore the contextual factors influencing EMR data quality, the system's role in supporting Smart Healthy City, and to develop strategic recommendations.



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The study was conducted at Dr. Sriningsih Primary Care Clinic (Klinik Pratama), which has implemented an EMR system. Data collection was carried out from March to May 2026. The clinic serves as a registered BPJS/JKN healthcare facility and represents a typical FKTP in an Indonesian mid-sized urban area.

Population and Sample

The study population comprised all EMR documents from patients registered at the clinic during the period January–December 2025. A total sampling technique was applied; all 150 EMR records that met the inclusion criteria (outpatient records with complete service episodes) were included. Records that were incomplete due to patient refusal or emergency circumstances were excluded.

Data Collection Instruments

Quantitative data were collected using a structured document audit checklist covering six quality dimensions with a total of 32 indicators. The checklist was developed based on Wang and Strong's (1996) data quality framework and Indonesian Minister of Health Regulation No. 24/2022 on Medical Records. For the qualitative component, a semi-structured interview guide was developed focusing on enabling/inhibiting factors, Smart Healthy City roles, and recommendations. Key informants included the clinic head and two healthcare staff members directly involved in EMR management.

Data Analysis

Quantitative data were analyzed descriptively by calculating the frequency and percentage of indicators met per dimension. Qualitative data were analyzed using thematic analysis: transcripts were read, coded, and grouped into themes reflecting enabling factors, inhibiting factors, and strategic recommendations. Data triangulation was performed by cross-validating findings from document audit, interviews, and policy document review to ensure validity and comprehensiveness.

RESULTS

3.1 EMR Data Completeness

Analysis of 150 EMR records across six documentation components revealed an overall completeness rate of 87.0%, with 13.0% categorized as incomplete. The results are presented in Table 1.

Table 1. EMR Data Completeness Analysis Results

No.	Component of Electronic Medical Records	Complete	Incomplete	Total	(%)
1	Patient Identity	145	5	150	**96.7%**
2	Anamnesis / Chief Complaint	140	10	150	**93.3%**
3	Physical Examination	132	18	150	**88.0%**
4	Diagnosis	128	22	150	**85.3%**
5	Treatment / Therapy	122	28	150	**81.3%**
6	Doctor / Healthcare Provider Signature	119	31	150	**79.3%**
	Overall Average	**130.5**	**19.5**	**150**	**87%**

Patient identity demonstrated the highest completeness (96.7%), followed by anamnesis/chief complaint (93.3%) and physical examination (88.0%). The lowest-performing component was doctor/healthcare provider signature at 79.3%, which is a concern given its legal and administrative significance in patient care documentation (14).

3.2 EMR Data Accuracy

The overall accuracy rate of EMR data reached 91.1%, with accuracy of patient name recording being the highest at 98.7%. Results are presented in Table 2.

Table 2. EMR Data Accuracy Analysis Results

No.	Accuracy Aspect of EMR Data	Accurate	Inaccurate	Total	(%)
1	Accuracy of Patient Name Recording	148	2	150	**98.7%**
2	Accuracy of Diagnosis Code (ICD-10)	135	15	150	**90.0%**
3	Consistency of Drug / Therapy Data	138	12	150	**92.0%**
4	Accuracy of Service Date & Time	142	8	150	**94.7%**
5	Validity of Laboratory Examination Results	120	30	150	**80.0%**
	Overall Average	**136.6**	**13.4**	**150**	**91.1%**

The most critical accuracy gap was found in laboratory examination data, where only 80.0% of records showed correct laboratory results. This discrepancy between physical laboratory outputs and digitally recorded values poses risks for clinical decision-making and treatment planning.

3.3 EMR Data Consistency

The overall consistency of EMR data reached 90.0%, with data entry timestamp consistency being the highest (98.7%). Results are presented in Table 3.

Table 3. EMR Data Consistency Analysis Results

No.	Consistency Aspect of EMR Data	Consistent	Inconsistent	Total	(%)
1	Data Entry Format Consistency	140	10	150	**93.3%**
2	Diagnosis Code Consistency Across Visits	132	18	150	**88.0%**
3	Patient Demographic Data Consistency	138	12	150	**92.0%**
4	Drug & Prescription Data Consistency	125	25	150	**83.3%**
5	Medical Procedure Recording Consistency	130	20	150	**86.7%**
6	Data Entry Date & Time Consistency	148	2	150	**98.7%**
	Overall Average	**135.5**	**14.5**	**150**	**90%**

Drug and prescription data consistency was the lowest at 83.3% (16.7% inconsistent), raising potential medication error concerns. Consistent data entry formats (93.3%) and demographic data (92.0%) indicate that standard operating procedures for basic EMR documentation are reasonably well understood by staff.

3.4 Timeliness of EMR Data Entry

The timeliness dimension achieved a perfect score across all five indicators, with 100% of all 150 records meeting the 24-hour data entry requirement. Results are presented in Table 4.

Table 4. Timeliness of EMR Data Entry Analysis Results

No.	Timeliness Aspect of EMR Data Entry	On Time	Not On Time	Total	(%)
1	Data entry within ≤24 hours after service	150	0	150	**100%**
2	Real-time data synchronization across system modules	150	0	150	**100%**
3	Timely patient status updates	150	0	150	**100%**
4	Accuracy of staff data entry timestamps	150	0	150	**100%**
5	Data availability when needed by clinicians	150	0	150	**100%**
	Overall Average	**150**	**0**	**150**	**100%**

This outstanding achievement indicates that Dr. Sriningsih Clinic has established strong data entry discipline, supported by automated reminder systems and strictly enforced standard operating procedures. Real-time synchronization across all system modules (100%) further demonstrates the reliability of the clinic's digital infrastructure.

3.5 EMR Data Security and Confidentiality

The overall security and confidentiality compliance rate reached 91.2%. User authentication scored highest at 98.7%, while audit trail implementation was the lowest at 80.0%. Results are presented in Table 5.

Table 5. EMR Data Security and Confidentiality Analysis Results

	Security & Confidentiality Aspect	Compliant	Non-Compliant	Total	(%)
1	User authentication system (username & password)	148	2	150	**98.7%**
2	Role-based access control (RBAC)	145	5	150	**96.7%**
3	Data encryption during transmission & storage	130	20	150	**86.7%**
4	Audit trail / user activity log	120	30	150	**80.0%**
5	Periodic data backup & system recovery	135	15	150	**90.0%**
6	Patient data confidentiality compliance	143	7	150	**95.3%**
	Overall Average	**136.8**	**13.2**	**150**	**91.2%**

Source: Primary Research Data, 2024

The incomplete audit trail coverage (80.0% compliance) poses a significant data governance risk, as comprehensive activity logging is essential for detecting unauthorized access and ensuring accountability. Data encryption during transmission reached 86.7%, indicating that some inter-module data transfers may still occur without full encryption — a vulnerability that requires urgent remediation.

3.6 EMR Data Integration

The overall data integration rate was 85.7%. Internal module integration and clinical history continuity showed strong performance, while external interoperability was notably lower. Results are presented in Table 6.

Table 6. EMR Data Integration Analysis Results

No.	Data Integration Aspect	Integrated	Not Integrated	Total	(%)
1	Integration across modules (outpatient, lab, pharmacy)	138	12	150	**92.0%**
2	Connectivity with BPJS/National Health Insurance	125	25	150	**83.3%**
3	Interoperability with other healthcare facilities	110	40	150	**73.3%**
4	Clinical history integration across visits	140	10	150	**93.3%**
5	Data reporting to Health Office / P-Care	130	20	150	**86.7%**
	Overall Average	**128.6**	**21.4**	**150**	**85.7%**

Interoperability with other healthcare facilities (73.3%) was the lowest-scoring indicator across all dimensions analyzed. Connectivity with the national BPJS/JKN system (83.3%) also indicates room for improvement. These integration gaps represent a significant barrier to achieving a cohesive Smart Healthy City health ecosystem.

3.7 EMR Data Quality Role in Supporting Smart Healthy City

The overall support rate of EMR data quality for Smart Healthy City implementation reached 85.9%. Digital access to health data was the highest-scoring indicator (93.3%). Results are presented in Table 8.

Table 8. EMR Data Quality Role in Supporting Smart Healthy City

No.	EMR Role Indicator in Smart Healthy City	Supporting	Not Supporting	Total	(%)
1	Digital access to residents' health data	140	10	150	**93.3%**
2	Support for evidence-based policy formulation	132	18	150	**88.0%**
3	Epidemiological monitoring & disease surveillance	128	22	150	**85.3%**
4	Enhanced inter-facility healthcare coordination	120	30	150	**80.0%**
5	Service efficiency & reduction of physical queues	138	12	150	**92.0%**
6	Contribution to integrated city health platform	115	35	150	**76.7%**
	Overall Average	**128.8**	**21.2**	**150**	**85.9%**

Contribution to integrated city health platforms (76.7%) and inter-facility coordination (80.0%) were the lowest-scoring indicators, reflecting the current silo nature of the clinic's EMR system. Despite strong internal data quality performance, external connectivity and participation in broader urban health ecosystems remain underdeveloped.

3.8 Overall EMR Data Quality Summary

Table 9 presents a consolidated overview of all six EMR data quality dimensions analyzed in this study.

Table 9. Overall Summary of EMR Data Quality at Clinic

No.	EMR Data Quality Dimension	Met Standard	Not Met	Sample	(%)
1	Completeness	130.5	19.5	150	**87.0%**
2	Accuracy	136.6	13.4	150	**91.1%**
3	Consistency	135.5	14.5	150	**90.0%**
4	Timeliness	150.0	0	150	**100%**
5	Security & Confidentiality	136.8	13.2	150	**91.2%**
6	Data Integration	128.6	21.4	150	**85.7%**
	Overall Average	**136.3**	**13.7**	**150**	**90.8%**

The overall average EMR data quality across all six dimensions reached 90.8%, indicating a good category of performance. Timeliness achieved the highest score (100%), while data integration was the area most requiring improvement (85.7%). All dimensions exceeded the 80% threshold, confirming that the clinic's EMR system provides a solid foundation for advancing digital health services.

The overall EMR data quality at Dr. Sriningsih Clinic (90.8%) is consistent with findings from similar primary care studies. Arabi et al. (2022) reported average EMR data quality scores of 85–92% in primary care facilities following structured EMR implementation programs, emphasizing the role of leadership commitment and staff training factors that align well with the present study's findings(14,15). The perfect timeliness score (100%) is particularly noteworthy and contrasts with commonly reported timeliness gaps in resource-constrained settings, where data entry delays of 24–72 hours are frequently documented (16,17).

The completeness rate of 87.0% aligns with WHO benchmarks for primary care EMR systems, which set a minimum threshold of 85% for key clinical documentation fields (18). However, the low completion rate for healthcare provider signatures (79.3%) is concerning, as electronic signatures carry legal and regulatory significance under Indonesian Minister of Health Regulation No. 24/2022. This finding is consistent with Kutney-Lee et al. (2021), who identified workflow interruptions and time pressure as primary drivers of signature documentation gaps in electronic health records (19).

The accuracy dimension (91.1%) demonstrates competent diagnosis coding practice, though laboratory result accuracy (80.0%) reveals a persistent integration challenge between point-of-care testing systems and the EMR database. This is a widely recognized interoperability problem in primary care settings where laboratory information systems (LIS) and EMR platforms operate with limited bidirectional data exchange protocols. Implementing HL7 FHIR-based integration between LIS and EMR modules would significantly reduce manual transcription errors and improve data accuracy(20).

The security dimension (91.2%) demonstrated generally strong performance, though the audit trail gap (80.0%) is a critical vulnerability in terms of data governance. The Indonesian Personal Data Protection Law (UU PDP No. 27/2022) requires comprehensive activity logging for all health information systems handling personal data. Incomplete audit trails not only create regulatory compliance risks but also undermine the accountability framework necessary for secure health data management in a Smart Healthy City context (21).

The integration dimension (85.7%) reveals the most significant development gap, particularly in external interoperability (73.3%). This finding parallels the challenges documented by Mullins et al. (2020) in their systematic review of EMR integration in healthcare settings, where intra-system connectivity typically outperforms inter-system connectivity due to proprietary data standards and fragmented digital infrastructure(22) . For Smart Healthy City implementation in Indonesia, integration with the SATUSEHAT platform and regional health dashboards is essential, requiring investment in FHIR-compliant APIs and health data exchange protocols (23).

The enabling and inhibiting factors identified in this study reflect the multidimensional nature of EMR quality governance. Management commitment (93.3%) as the strongest enabling factor is consistent with Renukappa et al. (2022), who identified executive-level leadership as the single most influential factor in smart healthcare strategy adoption (24). Conversely, high staff workload (66.7%) as the primary inhibiting factor aligns with James et al. (2020), who demonstrated that workflow integration efficiency significantly impacts EMR data quality through its effect on staff documentation behavior .

The overall Smart Healthy City support rate (85.9%) indicates that Clinic's EMR system provides a meaningful contribution to urban health data ecosystems, particularly through improved digital health access (93.3%) and service efficiency (92.0%). However, the low contribution to integrated city health platforms (76.7%) highlights the need for a structured digital health governance roadmap that connects primary care EMR systems with municipal and regional health information architectures(25). This finding is consistent that smart health implementations require seamless multi-layer data integration from clinical to population-level systems (26).

CONCLUSION

This study demonstrates that EMR data quality at Primary Care Clinic is categorized as good, with an overall average of 90.8% across six dimensions. Timeliness was the outstanding achievement (100%), reflecting strong organizational discipline in data entry. Completeness (87.0%), accuracy (91.1%), consistency (90.0%), and security (91.2%) all met acceptable standards, while data integration (85.7%) particularly external interoperability (73.3%) represents the primary area requiring strategic development. The EMR system meaningfully supports Smart Healthy City implementation (85.9%), with notable strengths in digital health access and service efficiency, though contribution to integrated urban health platforms requires enhancement. Key limitations of this study include its single-facility design, which restricts generalizability, and the cross-sectional data collection period, which does not capture longitudinal quality trends. Future research should examine multi-facility EMR quality comparisons and evaluate the effectiveness of FHIR-based interoperability interventions. Strategically, this clinic and similar primary care facilities are encouraged to prioritize: (1) implementation of automated EMR completion reminders; (2) full deployment of end-to-end data encryption and comprehensive audit trails; (3) development of FHIR for multi-facility interoperability; and (4) integration with regional SATUSEHAT platforms to support data-driven Smart Healthy City governance.

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