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Temporal Healthcare Data Warehouse with SCD Type 2 for OLAP-Based Executive Information Systems: A Galaxy Schema Approach

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Abstract. Modern hospital information systems operate within fragmented and heterogeneous OLTP environments designed for transaction recording rather than strategic analytical workloads. This study designs and implements a temporal healthcare Data Warehouse for OLAP analytics supporting historical data consistency and multidimensional performance monitoring aligned with Indonesian Ministry of Health (Kemenkes RI) standards. The Kimball bottom-up methodology was applied to integrate two heterogeneous OLTP sources into a Galaxy Schema comprising two fact tables and seventeen-dimension tables. The ETL pipeline was implemented using SSIS with a complete SCD Type 2 workflow preserving full patient dimension history across ward transfers and physician reassignments. The OLAP layer was constructed using SSAS Tabular with VertiPaq in-memory engine and DAX-based measures, visualized through a Power BI Executive Information System dashboard. Empirical validation using 52,321 discharged patient records over a one-year observation period demonstrated an average OLAP Speedup Ratio of 30.27× over equivalent relational SQL queries across ten benchmark runs, ranging from 2.98× (Slice) to 79.18× (Dice), with all response times below 40 ms and 100% computational accuracy across all six Kemenkes RI KPIs. The novelty lies in integrating a complete SCD Type 2 temporal model within a Galaxy Schema healthcare data warehouse, empirically validated against live heterogeneous hospital data and nationally aligned KPI standards.

Keywords: healthcare data warehouse, executive information system, OLAP, SCD Type 2, galaxy schema

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1. INTRODUCTION

The rapid growth of digital healthcare data has significantly transformed hospital information systems [1]. It is estimated that healthcare data accounts for approximately 30% of the total global data volume, with growth rates accelerating dramatically from doubling every three years in 2010 to approximately every 73 days in 2020 [2] [3]. This exponential growth introduces significant challenges in managing healthcare data, which is characterized by the five fundamental dimensions of Big Data: volume, velocity, variety, veracity, and value [4]. Traditional hospital systems relied on paper-based records or non-real-time systems, which often led to delays in reporting, data inconsistencies, and increased risks of operational errors [5]. In modern hospital environments, healthcare institutions manage heterogeneous data originating from multiple sources, including Electronic Health Records (EHR), laboratory systems, radiology systems, and administrative [6] at Figure 1. However, differences in data standards, terminologies, and formats create significant interoperability challenges, resulting in fragmented data and poor data quality [7].

Figure 1. Sources of big data in healthcare [1]

Data Warehouse (DW) architecture proviides a solution for integrating and managing heterogeneous healthcare data. A data warehouse enables the consolidation of data from multiple sources through processes such as extraction, transformation, cleansing, and integration into a centralized repository optimized for analytical processing, improving data consistency, reducing redundancy, and enhancing data accessibility for decision making [8] [9]. Online Analytical Processing (OLAP) enabling multidimensional analysis of large-scale healthcare data, OLAP supports analytical queries that allow users to explore trends, patterns, and performance indicators across multiple dimensions.

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Multidimensional data models, including star schema, snowflake schema, and fact constellation, are widely used to structure data efficiently for OLAP-based analysis [10].

Recent advancements in healthcare analytics have led to integrated frameworks such as Clinical Data Warehouses (CDW) and Executive Information Systems (EIS) that combine data integration, analytical processing, and visualization to support clinical and managerial decision-making [11], [12]. The integration of OLAP multidimensional modeling with standardized Key Performance Indicators (KPIs) has further strengthened the capacity of healthcare institutions to conduct longitudinal performance monitoring across time, ward, and patient demographic. However, limitations remain in existing implementations: many approaches address conceptual frameworks without resolving practical performance challenges such as query latency and scalability [13], [14]; SCD Type 2 for historical data versioning has not been fully optimized in healthcare systems [15]; and data integration across heterogeneous OLTP sources continues to produce reporting inconsistencies and reduced analytical reliability [6].

Therefore, this study proposes an integrated Data Warehouse and EIS architecture leveraging OLAP and SCD Type 2 modeling within a Galaxy Schema framework [16], implemented using the Microsoft BI stack: SSIS, SSAS Tabular, and Power BI [17] against real operational data from two heterogeneous OLTP sources. The central research question is: *to what extent can an OLAP-based architecture incorporating SCD Type 2 improve analytical query performance and KPI computational accuracy for hospital executive reporting compared to relational SQL approaches?* The study objectives are: (1) to design a Galaxy Schema integrating heterogeneous hospital data; (2) to implement SCD Type 2 for longitudinal patient dimension versioning; and (3) to develop an EIS dashboard aligned with Kemenkes RI standard KPIs.

The novelty of this study lies in three contributions distinguishing it from prior healthcare DW implementations. First, SCD Type 2 is implemented within a Galaxy Schema unlike prevailing Star Schema with SCD Type 1 approaches preserving full patient dimension history across ward transfers and physician reassignments, with deactivated versions (IsCurrent = 0, EndDate assigned) and active records maintained (IsCurrent = 1, EndDate = NULL), enabling longitudinal analysis unavailable in overwrite-based systems. Second, the architecture unifies two heterogeneous OLTP sources into a conformed

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dimensional model, addressing interoperability gaps identified in prior studies [6]. Third, all six Kemenkes RI standard KPIs such as BOR, LOS, TOI, BTO, GDR, NDR are directly embedded and validated within the OLAP model [16], providing a nationally aligned performance measurement framework for hospital executive reporting

2. METHODS

This study adopts a data engineering and system development approach to design and implement a healthcare data warehouse and Executive Information System (EIS) in 5 tier. **Figure 2** the methodology is structured into several sequential tier/stages, including data source, ETL processing, data warehouse modeling, OLAP analysis, and presentation. This approach follows established principles of dimensional modeling and business intelligence system development to ensure scalability, consistency, analytical performance in managing large-scale healthcare data.

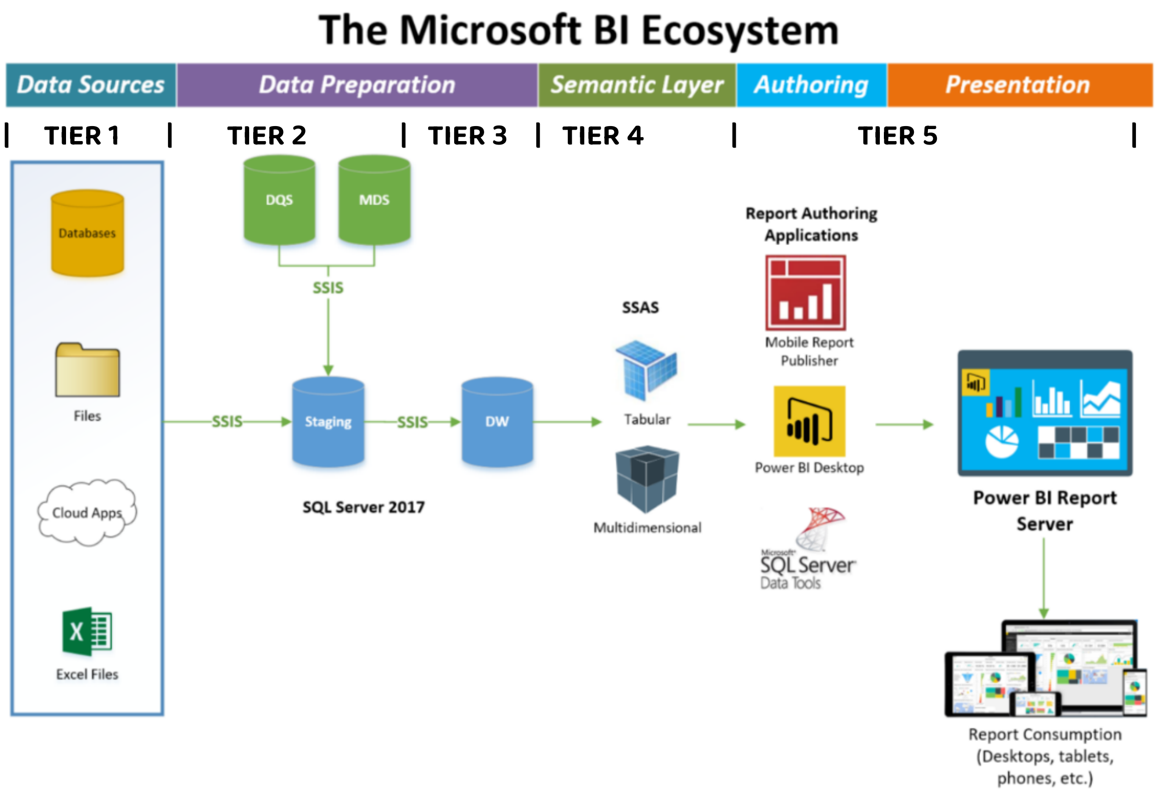

Figure 2. Architecture DW-EIS Microsoft BI Ecosystem [18]

2.1. Data Source and Study Area

The research was conducted at RSUD Prof. Dr. Margono Soekarjo, a hospital in Central Java. The data sources comprise heterogeneous healthcare records derived from two primary OLTP systems DBRS_MARGONO and SmartMedika both implemented on Microsoft SQL Server. The dataset covers a one year observation period from January 1, 2025 to December 31, 2025. This study utilized secondary data obtained from the hospital's internal information system infrastructure. All data processing activities were performed within the internal server environment, and the presentation layer, including dashboards and analytical reports, only displayed aggregated statistical indicators without exposing personally identifiable patient information to ensure data privacy.

2.2. Data Warehouse (DW) Design

The Data Warehouse was designed following the Kimball dimensional modeling methodology, adopting a bottom-up approach optimized for analytical decision support [19]. A Star Schema was excluded as it supports only a single fact table, while a Snowflake Schema was rejected due to excessive join complexity; the Galaxy Schema was therefore selected as it naturally accommodates multiple fact tables sharing conformed dimensions, consistent with the Fact Constellation principle [20]. The resulting schema comprises two central fact tables Fakta_RawatInap and Fakta_RawatJalan, recording outpatient encounter metrics supported by seventeen shared dimension tables enabling conformed analysis across both business processes [21]. SCD Type 2 was implemented across all dimension tables to preserve full historical versioning of time-variant patient attributes, ensuring analytical queries reflect the correct dimensional context at any historical point in time [15].

2.3. Extract–Transform–Load (ETL)

The ETL pipeline was implemented using SQL Server Integration Services (SSIS) to integrate heterogeneous data from two OLTP source systems DBRS_MARGONO and SmartMedika into the Data Warehouse [8]. During extraction, structural and format differences across source schemas were accommodated to enable unified data ingestion. In the transformation phase, data quality operations were applied including null-value handling, attribute normalization, code standardization, and deduplication. In the load phase, transformed data were incrementally loaded following the Galaxy Schema

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structure, with SCD Type 2 logic applied to track and preserve historical changes across all dimension tables [15].

2.4. OLAP and Analytical Modelling

Multidimensional analytical processing was conducted using SQL Server Analysis Services (SSAS) through a tabular data model, providing in-memory VertiPaq columnar compression for high-speed query execution. OLAP techniques support flexible data exploration across multiple dimensions, enabling roll-up, drill-down, slice, and dice operations [21]. Six hospital KPIs BOR, LOS, TOI, BTO, GDR, and NDR were defined as DAX measures within the tabular model in accordance with Indonesian Ministry of Health standards [22], [23]. The integration of SCD Type 2 within the OLAP model ensures historical consistency in analytical queries, preserving the integrity of time variant dimension attributes so that historical records remain aligned with their original values.

2.5. Executive Information System (EIS) Dashboard Development

The presentation layer was developed using Microsoft Power BI, delivering interactive dashboards tailored for executive-level users. Dashboards visualize the six hospital KPIs with dynamic filtering, time-based comparative analysis, and drill-through capabilities, enabling hospital management to monitor operational performance and support evidence-based strategic decision-making. Power BI's native connectivity with the SSAS tabular model ensures seamless data refresh and real-time synchronization with the DW [17].

2.6. System Evaluation

System evaluation was conducted through a structured three-tier quantitative framework to assess functional correctness, KPI computational accuracy, and analytical performance of the proposed Data Warehouse and OLAP-based Executive Information System. This framework was intentionally scoped to technical and computational validation, comprising three sequential stages: black-box functional testing, SQL–DAX computational verification, and OLAP query-performance benchmarking. Formal User Acceptance Testing (UAT) involving hospital executives or operational end-users was not conducted within this study, as the primary objective was to validate the technical feasibility and performance of the proposed architecture; UAT is therefore identified as a necessary direction for future investigation.

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2.6.1. Functional Validation

Functional correctness was verified through black-box testing by validating system inputs and outputs against predefined functional specifications without reference to the internal implementation logic. The evaluation covered all major workflows of the proposed system, including ETL execution, SCD Type 2 versioning, OLAP query processing, KPI computation, and dashboard rendering. Each test case was considered successful when the actual system output matched the expected functional behavior specified during system design.

2.6.2. KPI Computational Accuracy

The accuracy of the OLAP tabular model in computing hospital performance indicators was validated by comparing SSAS-derived KPI values against SQL-based reference calculations obtained directly from the source relational database. Six standard hospital KPIs were evaluated in accordance with the Indonesian Ministry of Health (Kementerian Kesehatan Republik Indonesia) reporting standards [22], [23]:

1) Bed Occupancy Rate (BOR)

BOR measures the proportion of available bed-days that are actually occupied by inpatients during a given period Reference Kemenkes RI [22]: 60–85% at Equation 3:

$$\text{BOR}= \frac{\text{Total Inpatient Care Days}}{\text{Avilable Beds x Observation Period (days)}} \text{ x } 100\% \tag{3}$$

2) Length of Stay (LOS)

LOS measures the average number of days a patient occupies an inpatient bed per admission Reference standard Kemenkes RI [22]: 6–9 days at Equation 4:

$$\text{LOS}= \frac{\text{Total Inpatient Care Days}}{\text{Total Discharged Patients (live + death)}} \tag{4}$$

3) Turnover Interval (TOI)

TOI measures the average number of days a bed remains unoccupied between two successive inpatient admissions. Reference standard Kemenkes RI [22]: 1–3 days at Equation 5:

$$\text{TOI}= \frac{\text{(Available beds x period days) - Total Inpatient Care Days}}{\text{Total Discharged Patients (live + death)}} \tag{5}$$

4) Bed Turnover Rate (BTO)

BTO measures the frequency with which each available bed is used within a given observation period standard Kemenkes RI [22]: 40–50 times per year Equation 6:

$$\text{BTO}= \frac{\text{Total Discharged Patients}}{\text{Available beds}} \tag{6}$$

5) Gross Death Rate (GDR)

GDR measures the overall mortality rate per 1,000 discharges, including deaths within 48 hours of admission standard Kemenkes RI [22]: < 45‰ at Equation 7:

$$\text{GDR}= \frac{\text{Total Deaths (all causes)}}{\text{Total Discharged Patients}} \times 1000‰ \tag{7}$$

6) Net Death Rate (NDR)

NDR measures mortality among patients who survived at least 48 hours of inpatient care, reflecting care quality more precisely than GDR standard Kemenkes RI [22]: < 25‰ at equation 8:

$$\text{NDR}= \frac{\text{Deaths after >48 hours of admission}}{\text{Total Discharged Patients}} \times 1000‰ \tag{8}$$

2.6.3 OLAP Query Response Time

Query performance was evaluated by comparing the response time of equivalent analytical queries executed on the relational SQL data warehouse and the SSAS tabular OLAP model. Response time was measured using DAX Studio 3.0.8 on Equation 9 [25], where response time is defined as difference between query completion and query start time. Five representative OLAP operations (slice, roll-up, drill-down, dice, and SCD Type 2 join) were executed ten times and the average response time was used for analysis.

$$\text{Response Time}= t_{end} - t_{start} \text{ (miliseconds, ms)} \tag{9}$$

Performance improvement was quantified using the Speedup Ratio in Equation 10 [24], calculated as the ratio between SQL response time and OLAP response time. A Speedup Ratio greater than 1 indicates that the OLAP model provides faster analytical query execution than the equivalent relational SQL approach.

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$$\text{Speedup Ratio}=\frac{\text{Response Time}_{SQL}}{\text{Response Time}_{OLAP}} \quad (10)$$

3. RESULTS AND DISCUSSION

3.1. Extract–Transform–Load (ETL) Pipeline Implementation

The ETL process was successfully implemented using SQL Server Integration Services (SSIS), integrating heterogeneous data from two primary OLTP source systems DBRS_MARGONO and SmartMedika into the Data Warehouse. As illustrated in **Figure 3**, the SSIS control flow orchestrates multiple sequential data integration packages covering all dimension tables, including Dimensi_Agama, Dimensi_Pendidikan, Dimensi_Jenis Kelamin, Dimensi_CaraMasuk, Dimensi_Dokter, and Dimensi_Ruang. Each package comprises two sequential sub-tasks: a Database Staging phase that extracts and temporarily buffers raw source records, followed by a Data Warehouse loading phase that applies transformation logic and populates the target dimensional tables.

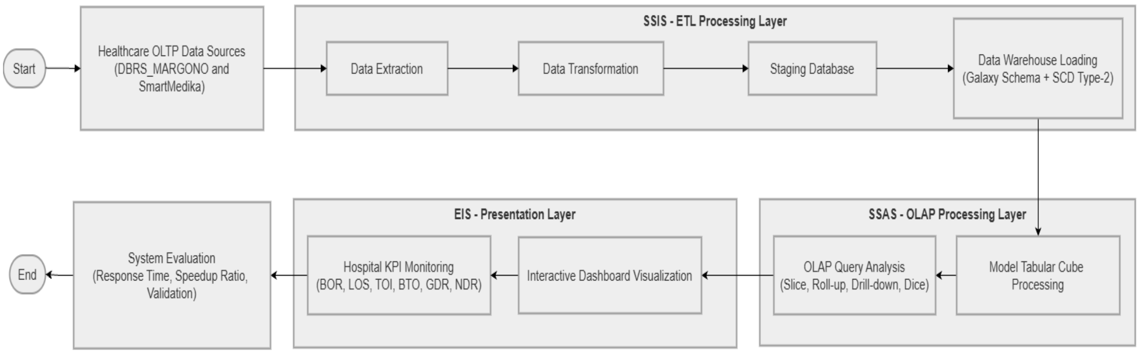

Figure 3. Pipeline research implementation

3.2. Slowly Changing Dimension Type 2

The detailed for SCD Type 2 implementation is illustrated example at **Figure 4**. This pipeline architecture ensures that every dimension attribute change is preserved as a new versioned record rather than overwriting the existing one the defining behavior of SCD Type 2. Data from the DBRS_MARGONO and SmartMedika systems were extracted, transformed, and loaded into the Data Warehouse. During the loading phase, the SCD Type 2 mechanism was implemented using Lookup (IsCurrent = 1), Conditional Split (new, unchanged, and changed records), OLE DB Command (to update EndDate and set IsCurrent = 0), and Derived Column transformations.

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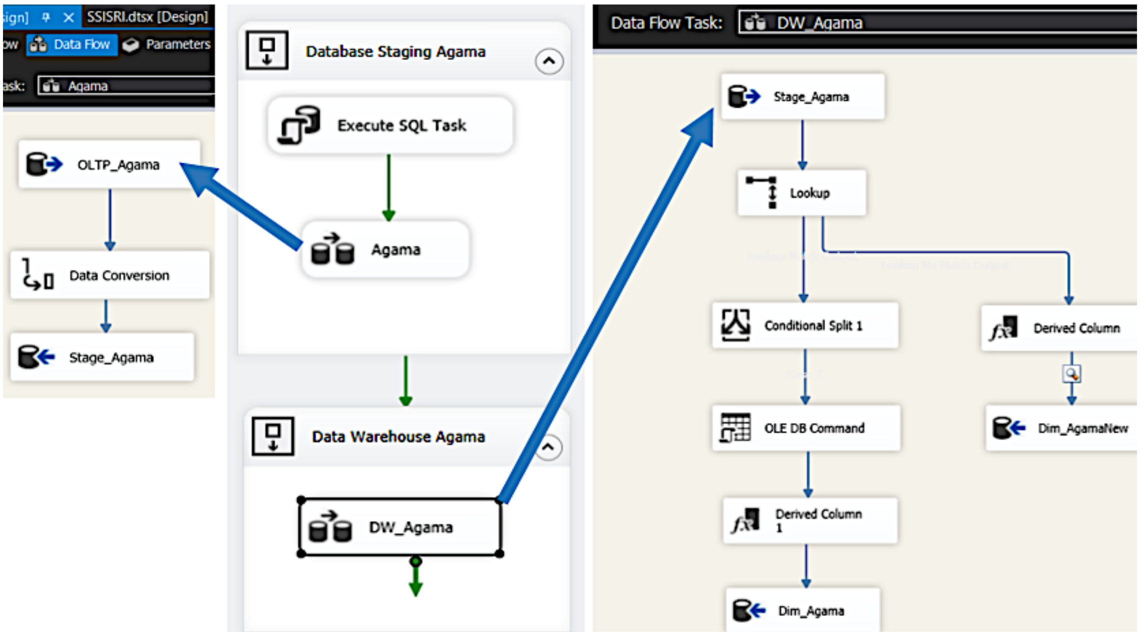

Figure 4. SSIS ETL and SCD Type 2

The correctness of the SCD Type 2 implementation is empirically demonstrated through versioned records of a single patient (PasienId: 02299420, RegistrasiId: 2501020607), as presented in Figure 5. The sequence captures two successive dimension changes: a ward transfer from RuangId 9304 to 9303, followed by a doctor from D270 to D268, with each change triggering deactivation of the prior record (IsCurrent = 0, EndDate assigned) and insertion of a new active version (IsCurrent = 1, EndDate = NULL).

	Id_Rawatinap	RegistrasiId	PasienId	RuangId	Dokter	StartDate	EndDate	IsCurrent
52	3455	2501020607	02299420	9304	D270	2026-03-30 12:30:01.120	2026-03-30 14:00:31.730	0
53	3456	2501020607	02299420	9303	D270	2026-03-30 14:00:31.730	2026-05-22 10:02:15.077	0
54	320871	2501020607	02299420	9303	D268	2026-05-22 10:02:15.077	NULL	1

Figure 5. Type 2 Slowly Changing Dimensions

3.3. Data Warehouse Schema

The implemented Galaxy Schema integrating two fact tables and seventeen-dimension tables is presented in Figure 6. The adoption of a Galaxy Schema over the single star schema commonly reported in prior healthcare DW studies enables dimensional reusability across both fact domains and supports conformed cross-domain OLAP queries consistent with the Fact Constellation principle advocated by Inmon [20]. The normalization of Dimensi_Pasien into eight sub-dimension tables reduces attribute redundancy while preserving referential integrity [26] for complex healthcare dimensional models.

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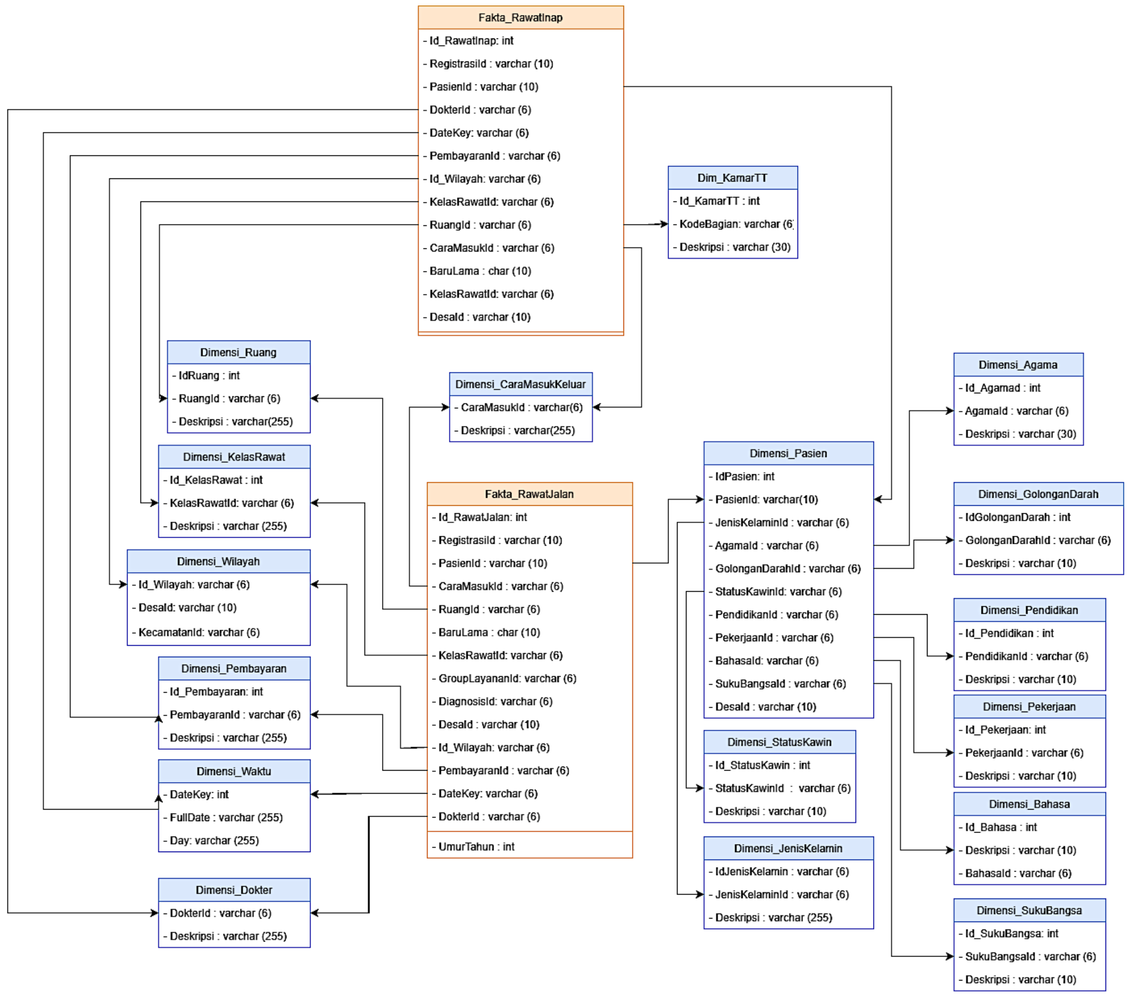

Figure 6. Datawarehouse Galaxy Scheme

3.4. Functional Validation Result

Functional validation was conducted through black-box testing to verify that all major system components operated in accordance with their predefined functional specifications. Testing covered five core workflows of the proposed system. Each workflow was evaluated by comparing actual system outputs against expected behavior defined during system design. Table 1 presents the summary results.

Table 1. Black-Box Functional Validation Results

Test Case	Description	Status
ETL Execution	SSIS packages successfully ETL data from both OLTP sources into the Data Warehouse. NULL handling, deduplication, and incremental loading operated without error.	✓ Pass

Test Case	Description	Status
SCD Type 2 Versioning	New and modified dimension records were correctly versioned. Prior versions deactivated (IsCurrent = 0, EndDate assigned); new versions were inserted (IsCurrent = 1, StartDate = load date)	✓ Pass
OLAP Query Processing	All five analytical operation types : Slice, Roll-up, Drill-down, Dice, and SCD Type 2 Join, returned results consistent with expected aggregates and filter contexts	✓ Pass
KPI Computation	All six DAX-based KPI measures (BOR, LOS, TOI, BTO, GDR, NDR) produced values identical to SQL-based reference calculations, with zero absolute deviation across all indicators	✓ Pass
Dashboard Rendering	The Power BI EIS dashboard correctly rendered all KPI cards, charts, and tables. Dynamic filtering via year slicer and drill-through navigation to ward-level detail pages	✓ Pass

3.5. KPI Computational Accuracy Validation

The computational accuracy of the SSAS tabular model was validated by comparing KPI values generated by DAX measures against SQL-based reference calculations executed directly against the relational data warehouse. SQL reference queries were constructed as semantically equivalent T-SQL statements implementing each KPI formula in accordance with Indonesian Ministry of Health (Kemenkes RI) standards [22]. Both computation methods were applied to identical source data: the 2025 observation period (January 1 – December 31, 2025), with a validated bed capacity of 869 beds and a standardized 365 day period. The underlying operational parameters used in both computations are presented in Table 2.

Table 2. Hospital Operational Parameters for KPI Validation from OLAP Model (2025)

Parameter	Value
Total Inpatient Care Days (HariPerawatan)	283,221
Total Inpatient Patients (JumlahPasienRI)	52,321
Total Discharged Patients (PasienKeluar)	52,321
Total Mortality — All Causes (TotalMeninggal)	4,141
Mortality > 48 Hours (MeninggalLebih48Jam)	3,287

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Parameter	Value
Mortality < 48 Hours (MeninggalKurang48Jam)	859
Total Beds (JumlahTT)	869
Observation Period (JumlahHari)	365

Table 3 presents the complete validation results. For each KPI, the SQL-based reference value and the OLAP DAX-derived value are compared, with the absolute difference and resulting accuracy reported.

Table 3. KPI Accuracy Validation: SQL-Based Reference vs. OLAP (SSAS Tabular)

KPI	SQL-Based	OLAP (DAX)	Difference	Accuracy (%)
BOR (%)	89.29	89.29	0.00	100.00
LOS (days)	5.41	5.41	0.00	100.00
TOI (days)	0.65	0.65	0.00	100.00
BTO (per year)	60.21	60.21	0.00	100.00
GDR (‰)	79.15	79.15	0.00	100.00
NDR (‰)	62.82	62.82	0.00	100.00

3.6. OLAP Query Performance

The analytical performance of the proposed OLAP model was evaluated by comparing the response time of equivalent analytical queries executed on the relational SQL data warehouse and the SSAS Tabular model under identical hardware and software environments, as specified in Table 4.

Table 4. Benchmark Testing Environment Specification Windows Server

Parameter	Value
Processor	Intel Xeon Gold 6234 CPU @ 3.30 GHz (4 vCPU)
RAM/ Memory	32 GB DDR4
Operating System	Windows Server 2022 Datacenter 64-bit
Database Engine	Microsoft SQL Server 2022
OLAP Engine	SQL Server Analysis Services (SSAS) Tabular
ETL Tool	SQL Server Integration Services (SSIS)

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Parameter	Value
Query Tool — SQL	SQL Server Management Studio (SSMS)
Query Tool — OLAP	DAX Studio 3.0.8
Observation Year	2025
Inpatient Records	52,321
Number of Runs per Query	10

Five representative analytical operations were selected to reflect common executive reporting requirements: Slice, Roll-up, Drill-down, Dice, and SCD Type 2 Analysis. Each operation was implemented as both a T-SQL query against the relational data warehouse and a semantically equivalent DAX expression against the SSAS Tabular model, with result-set equivalence verified prior to measurement. Each query was executed ten times independently only under warm-cache conditions meaning the database engine and OLAP engine had been initialized and previously accessed prior to measurement to ensure stable and reproducible response times. The average response time was computed using Equation (1), and the Speedup Ratio was calculated using Equation (2). Warm-cache benchmarking represents an inherent limitation of this study, as it reflects optimized steady-state performance rather than cold-start latency; this is acknowledged in Section 3.7 Limitation.

The five operations cover the following analytical scenarios. The Slice operation filters the inpatient fact table by year (2025), returning aggregated patient count and care days per ward. The Roll-up operation aggregates inpatient episodes from monthly to annual level across the time hierarchy. The Drill-down operation traverses the geographic hierarchy from province to district level via SCD Type 2 versioned patient dimension records. The Dice operation applies simultaneous filters across ward, payment type, and observation period. The SCD Type 2 Analysis operation evaluates temporal consistency of versioned patient dimension records for Q1 2025. Detailed response time measurements across all ten runs are presented in Table 5, and the comparative summary is presented in Figure 6.

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Table 5. Presents the detailed response time measurements across all ten runs

Run / Query	Slice SQL	Slice OLAP	Roll-up SQL	Roll-up OLAP	Drill-down SQL	Drill-down OLAP	Dice SQL	Dice OLAP	SCD Type 2 SQL	SCD Type 2 OLAP
Run 1	69	22	74	2	450	9	165	1	805	32
Run 2	67	23	65	7	386	10	177	3	831	40
Run 3	68	19	65	5	371	13	168	1	820	43
Run 4	70	26	71	4	452	12	191	3	821	41
Run 5	69	25	75	7	395	15	170	3	805	37
Run 6	67	21	63	5	392	11	168	2	803	35
Run 7	70	23	77	5	372	12	166	2	808	42
Run 8	69	21	70	6	391	11	174	3	837	35
Run 9	70	25	75	5	410	13	182	2	831	39
Run 10	67	25	65	4	391	12	181	2	832	42
Avg (ms)	**68.60**	**23.00**	**70.00**	**5.00**	**401.00**	**11.80**	**174.20**	**2.20**	**819.30**	**38.60**
Ratio	**-**	**2.98×**	**-**	**14.00×**	**-**	**33.98×**	**-**	**79.18×**	**-**	**21.23×**

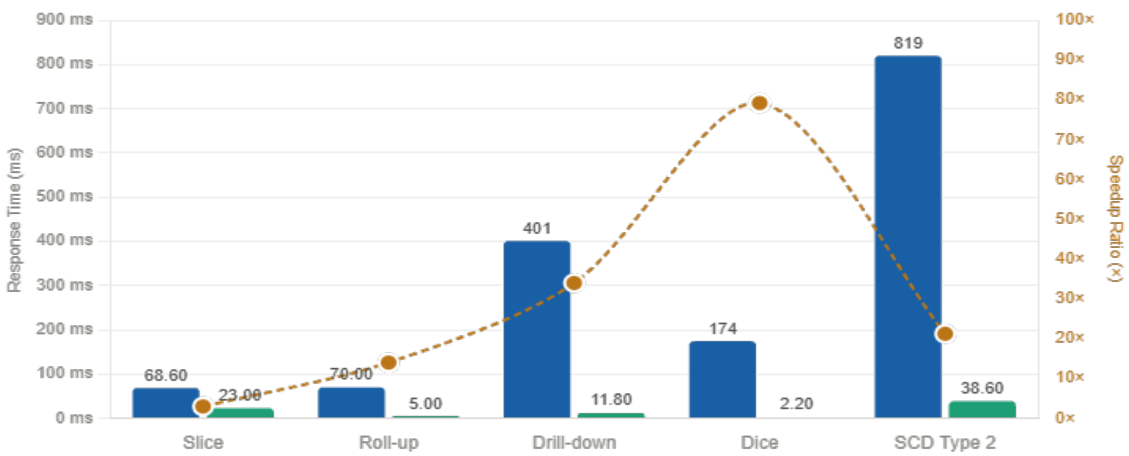

Figure 6. Response Time Comparison: OLAP SSAS (blue) VS OLTP SQL (green) ten runs

As illustrated in Figure 6, the SSAS Tabular model consistently outperformed the relational SQL approach across all five operations, achieving an average Speedup Ratio of **30.27×.** The highest gain was observed in the Dice operation (79.18×), attributable to VertiPaq pre-aggregated columnar structures enabling simultaneous multi-dimensional filtering, while the lowest was Slice (2.98×) due to its simpler single-dimension structure.

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All OLAP response times ranged from 2.20 ms to 38.60 ms, well below the 100 ms perceptual instantaneity threshold [25].

3.7. Hospital KPI Computation via OLAP Tabular Model

The SSAS Tabular model successfully computed all six Kemenkes RI standard KPIs from 52,321 discharged patient records across the 2025 observation period in Table 6. The convergence of elevated BOR (89.29%), BTO (60.21), and TOI (0.65 days) collectively indicates structural overcapacity at RSUD Prof. Dr. Margono Soekarjo, characteristic of high-volume public referral hospitals under sustained demand pressure. The LOS of 5.41 days near the recommended range warrants further stratified clinical investigation to distinguish efficient throughput from capacity-induced early discharge. The GDR (79.15‰) and NDR (62.82‰) exceed Kemenkes RI thresholds and must be interpreted within the referral hospital context.

Table 6. Hospital KPI Computation Results (2025)

KPI	Value	Standard
BOR (%)	89.29%	60–85%
LOS (days)	5.41	6–9 days
TOI (days)	0.65	1–3 days
BTO (per year)	60.21	40–50
GDR (‰)	79.15‰	< 45‰
NDR (‰)	62.82‰	< 25‰

3.8. Limitations

This study has several limitations. First, the implementation was conducted using data from a single hospital over a one-year observation period, which may limit the generalizability of the findings to other institutional contexts. Second, UAT involving hospital executives and operational end-users was not conducted; user satisfaction, usability, and decision-support effectiveness therefore remain unevaluated. Third, query performance benchmarks were conducted exclusively under warm-cache conditions, reflecting optimized steady-state performance rather than cold-start latency; the reported Speedup Ratio of 30.27× should therefore be interpreted as an indicative upper-bound estimate under controlled conditions rather than a guarantee of equivalent gains

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in production environments. Fourth, it is important to distinguish that the benchmark measures analytical query response time and does not represent data refresh latency; the current ETL pipeline operates on a scheduled refresh basis and does not support near-real-time or streaming data ingestion. Fifth, the architecture relies entirely on the Microsoft BI ecosystem, which may constrain portability to organizations operating under different technology platforms.

4. CONCLUSION

This study successfully designed and implemented an integrated Data Warehouse and OLAP-based Executive Information System incorporating SCD Type 2 modeling within a Galaxy Schema framework at RSUD Prof. Dr. Margono Soekarjo. Black-box testing confirmed 100% pass rate across all five workflows, and SQL–DAX verification established zero deviation across all six Kemenkes RI KPIs, confirming full numerical integrity throughout the analytical pipeline. Query benchmarking across ten runs achieved a mean Speedup Ratio of 30.27× over relational SQL, with all OLAP response times below 40 ms including the SCD Type 2 temporal join operation confirming that historical versioning does not compromise EIS interactivity. KPI analysis from 52,321 discharged patient records revealed structural overcapacity (BOR 89.29%, LOS 5.41 days, TOI 0.65 days, BTO 60.21), with GDR (79.15‰) and NDR (62.82‰) substantially exceeding Kemenkes RI thresholds, warranting risk adjusted mortality analysis directly supported by the implemented OLAP drill-down functionality. This study is limited to a single hospital, one year observation period, warm cache benchmarking conditions, and absence of UAT, which may constrain generalizability and operational completeness of the findings. Future work should prioritize UAT with hospital executives, multi-institutional validation, predictive analytics integration, and near-real-time streaming data ingestion.

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