
Designing a Data Mart at the Indonesian Psychological Healthcare Center Using Pentaho

DOI: <http://dx.doi.org/10.35889/jutisi.v14i3.3153>

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Abstrak

Critical data is essential for organisational success, providing essential information for decision-making. This study focuses on the Indonesian Mental Health Centre (IndoPsyCare), which utilises data to improve service performance. The research aims to design a data mart to support analytical needs by transforming the Online Transaction Processing (OLTP) database into Online Analytical Processing (OLAP). This design follows Kimball's Nine-Step Approach and integrates the Extract, Transform, Load (ETL) process. Data was collected from August 2023 to August 2024 through interviews and electronic documentation. The system was implemented using Microsoft SQL Server Management Studio 18 and Pentaho Data Integration. The resulting data mart uses a star schema with fact and dimension tables tailored to stakeholder needs, particularly in appointment analysis. Findings indicate that the data mart facilitates efficient access, targeted analysis, and improved query performance, thereby supporting IndoPsyCare's decision-making and overall service optimisation.

Keywords: Dashboard; Extract Transform Load; Nine-Step Kimball; Online Analytical Processing; Pentaho Data Integration.

1. Introduction

With the advancement of technology, information plays a very important role for a company [1], [2]. Transactions that occur within the company must be processed quickly so they can be used by stakeholders for business processes [3]. In this context, a database plays a crucial role in systematically managing company data [4]. The sustainability of a company is determined by the availability of complete, easily accessible, and accurate data [5]. A company's transactional data is generally stored in an Online Transaction Processing (OLTP) database. In this database, data is updated in real-time according to the transactions taking place within the company. However, without proper analytical systems, the potential value of this data often remains untapped, limiting its contribution to strategic decision-making [4], [5]. Therefore, research on optimising data management and analysis systems remains a critical area to explore.

The Indonesian Psychological Healthcare Center, hereinafter referred to as IndoPsyCare, utilizes available data to continuously improve its service performance. IndoPsyCare itself is a mental health service based in South Jakarta [6]. Mental health services play an important role as an effort to address mental health disorders [7]. Through mental health services, individuals can meet their psychological needs with the assistance of psychologists [8], [9]. This urgency is also one of the reasons for the establishment of IndoPsyCare. Despite the

growing demand, IndoPsyCare faces challenges in utilising its transactional data effectively. Data from patient appointment transactions, which include booking frequency, cancellations, and consultation durations, are stored operationally in OLTP systems but are not yet fully analysed to support managerial insights. This limits IndoPsyCare's ability to measure service efficiency, monitor patient trends, and plan strategic improvements in mental health care delivery. The measurable issue lies in the lack of integrated data analysis that can support cost estimation, service demand forecasting, and performance evaluation, which are key metrics in service optimisation [4], [9].

This study designs a data mart aimed at providing accurate and relevant data for IndoPsyCare stakeholders. The data is used by stakeholders to analyze information and as a supporting tool in the decision-making process. One of the data points that IndoPsyCare intends to analyze is the estimated costs that patients need to prepare for making an appointment. This allows patients to plan their expenses to access IndoPsyCare's mental health services. This strategy is part of IndoPsyCare's efforts to improve its service performance. Using the Nine-Step Kimball methodology, which has proven effective in multiple sectors including education [17], healthcare [18], and industry [19], the research aims to transform IndoPsyCare's OLTP data into an Online Analytical Processing (OLAP) system. This approach enables multidimensional data analysis, improving data retrieval performance and analytical depth. The implementation of the Extract, Transform, Load (ETL) process using Pentaho Data Integration further ensures accurate, clean, and reliable data for stakeholder use [14], [21], [24]. The rationale for adopting Kimball's method lies in its scalability, structured development stages, and compatibility with business intelligence tools widely used in healthcare informatics. A data mart is a component of a data warehouse that focuses on specific business processes [10]. In a data warehouse, large volumes of historical data are stored in a database to support data analysis and decision-making processes [11]. This database becomes an Online Analytical Processing (OLAP) database, serving as the system schema foundation for data warehousing. The design of a data mart involves the Extract, Transform, Load (ETL) process, which populates fact tables and dimension tables [12]. These tables are part of the OLAP database and also represent the data mart schema. Analysis using an OLAP database enhances data processing speed. With a data mart, analysis is specifically focused on certain business areas.

Accordingly, this research aims to design a data mart that provides structured analytical data for IndoPsyCare's decision-making processes. In this study, IndoPsyCare focuses on appointment transactions conducted by patients through the IndoPsyCare website. The expected outcomes include improved accuracy and accessibility of analytical data, enabling management to evaluate performance metrics, forecast demand, and plan cost-efficient mental health services. Moreover, this research contributes to expanding the application of data mart design and business intelligence principles in the mental healthcare sector in Indonesia.

2. Literature Review

Previous studies have highlighted the importance of data warehouse and data mart design in supporting organisational decision-making. Sutanto et al. [1] developed a sales system using the Point-of-Sale approach, demonstrating how data management can improve business processes. Similarly, Louis et al. [2] designed a business intelligence dashboard for pharmacy accounts receivable, emphasising the role of structured data in supporting financial decision-making.

Several studies have applied Kimball's methodology in data warehousing design. Prior studies that used Kimball/Nine-Step provide methodological precedent [3], [10], [19]. The present study follows these established steps but applies them to appointment transactions in a mental-health clinic, rather than to retail or export-import domains.

Akbar and Rahmanto [3] applied the Nine-Step Methodology to sales data, while Priono et al. [10] used the same approach for export-import data, confirming its efficiency in transforming Online Transaction Processing (OLTP) into Online Analytical Processing (OLAP). Anshari and Retno [19] also used Kimball's method to process historical business data, reinforcing its application in the context of business intelligence. Research in the fields of health and psychology also recognises the importance of data-driven systems. Angela et al. [4] designed a dashboard for mental health appointments, while Finandi et al. [16] applied OLAP to healthcare services in diabetes management. Delgado et al. [18] expanded this approach by implementing business intelligence in healthcare organisations using the Kimball methodology, demonstrating its

suitability in a clinical context. His works to emphasise BI/dashboard benefit, this study extends those outcomes by documenting the data-mart engineering choices and ETL pipelines that enable reliable dashboards. Where dashboard studies stop at visualisation requirements, this paper describes surrogate key strategies, SCD handling options, and pre-calculation storage—details necessary for reproducibility. In terms of technical development, Hamoud et al. [12] demonstrated the value of independent educational data marts, while Sihombing [17] modelled an academic data warehouse using the Nine-Step Method. Wardhani and Wiratama [24] further showed how the implementation of Extract, Transform, Load (ETL) improves service quality in the pharmaceutical industry and demonstrates an integrated pipeline using Pentaho Data Integration together with Microsoft SQL Server for storing the target data mart. Complementary works also explore ETL optimisation, including efficient incremental loading [21] and cloud-based ETL processes [22].

From the reviewed literature, it is clear that the Kimball methodology and OLAP have been widely applied across various sectors such as retail, education, and healthcare. However, existing research has primarily focused on general business operations or specific clinical domains, without considering mental health service providers in Indonesia. This study updates the current state by designing a data mart tailored to IndoPsyCare appointment transactions, integrating OLTP to OLAP transformation through Pentaho Data Integration. Unlike previous studies [3], [10], [18] that emphasise generic datasets, this study offers conceptual uniqueness by targeting mental health services, aligning structured data analysis with stakeholder needs in performance monitoring and decision-making.

The state of the art of this research demonstrates the successful application of the Kimball Nine-Step methodology for transforming OLTP data into OLAP structures across diverse sectors such as retail, education, and general healthcare [3], [10], [17], [18]. Studies have also highlighted the role of OLAP and ETL tools in supporting clinical reporting and service quality improvement [16], [21], [24]. However, few investigations have focused specifically on mental-health service providers, particularly within the Indonesian context. The novelty of this study lies in the design of an appointment-centric data mart tailored to IndoPsyCare's mental-health services, integrating cost-estimation and service-performance indicators into the fact table. Moreover, the study provides a reproducible implementation of the Nine-Step Kimball process using Pentaho Data Integration and Microsoft SQL Server, offering a practical and domain-specific contribution to data-mart development for healthcare decision support.

3. Methods

This study uses interviews and electronic documents to collect historical data. The data mart design is carried out using the Nine-Step Kimball method, which involves the Extract, Transform, Load (ETL) process. The research workflow begins with source data from an Online Transaction Processing (OLTP) system in Microsoft SQL Server Management Studio (SSMS) 18. SSMS is a Database Management System (DBMS) that manages relational databases and supports the implementation of business intelligence [13]. The data then undergoes the ETL process using the Pentaho Data Integration (PDI) tool, transforming it into Online Analytical Processing (OLAP) data. Pentaho enables users to perform data extraction, transformation, and loading [14]. The resulting data mart is stored in Microsoft SQL Server Management Studio 18.

3.1. Data Collection

The data used for designing the data mart is collected through interviews and electronic documents. An interview is a method of gathering information by asking questions verbally, to which responses are also given verbally [15]. In this study, interviews were conducted with Indonesian IndoPsyCare representatives to obtain information regarding the company's needs.

From the interviews, it was found that IndoPsyCare aims to analyze available data and use it as a supporting tool in decision-making. To achieve this, the researcher designed a data mart to produce structured data that supports stakeholder analysis processes. The data used was obtained from IndoPsyCare's electronic documents, specifically patient appointment transaction data. The data covers a one-year period, from August 2023 to August 2024. The transactional database, commonly referred to as Online Transaction Processing (OLTP), used to manage transaction data, is stored in Microsoft SQL Server Management Studio 18.

3.2. Data Mart Design

The data mart is designed to produce an Online Analytical Processing (OLAP) database to accelerate data retrieval and analytical processes [16]. In this study, the Nine-Step Kimball method is used to design the data mart, which includes the Extract, Transform, Load (ETL) process.

3.3. Nine-Step Kimball Methodology

This study employs the Nine-Step Kimball method to design a data warehouse. A data warehouse is essentially a large-scale data mart [10]. This method is widely used due to its advantages, including easy-to-understand stages, perceived effectiveness, and relatively low development costs [17]. The information presented through the stages of this method is structured and sufficient to provide value to its users [18]. Below are the nine stages of data warehouse development using the Nine-Step Kimball method [19].

1) Choose the Process

The first stage involves determining the focus of the business process that will serve as the main subject in developing the data mart. Patient transactions when scheduling appointments on the IndoPsyCare website are the primary subject in designing the data mart.

2) Choose the Grain

In this stage, the entities to be represented in the fact table are determined. The grain is obtained from the IndoPsyCare OLTP transaction database. The following master data will be used to design the data mart:

- a) Category: Data defining the category of the patient when making an appointment to receive mental health services.
- b) Client: Data identifying the patient making the appointment.
- c) Company Partner: Data about companies that collaborate with IndoPsyCare.
- d) Location: Data on the locations where IndoPsyCare provides services to patients.
- e) Provider: Data on the psychologists registered at IndoPsyCare.
- f) Service: Data about the types of services offered by IndoPsyCare, along with their prices.
- g) Transaction: Data on the patient's transaction when making an appointment.

3) Identify and Conform to the Dimensions

In this stage, dimension tables are identified and subsequently linked to the fact table. Below are the dimension tables in the designed data mart:

- a) **Category Dimension:** Consists of sk_category, category_code, and category_name.
- b) **Client Dimension:** Consists of sk_client, client_code, and client_name.
- c) **Company Dimension:** Consists of sk_company, company_code, and company_name.
- d) **Location Dimension:** Consists of sk_location, location_code, and location_name.
- e) **Provider Dimension:** Consists of sk_provider, provider_code, and provider_name.
- f) **Service Dimension:** Consists of sk_service, service_code, service_name, category_code, and price.
- g) **Time Dimension:** Consists of sk_time, appointment_date, day, month, and year.

4) Choose the Facts

This stage determines the fact table in designing the data mart. The fact to be created in the data mart is the transaction fact, derived from the appointment transaction process. The transaction fact consists of the following fields: sk_category, sk_client, sk_company, sk_location, sk_provider, sk_service, sk_time, total_appointment, total_cancel, and total_duration.

5) Store Pre-calculation in the Fact Table

This stage involves considering the calculations of an attribute before it is loaded into the data mart. The calculations stored in the data mart include total_appointment, total_cancel, and total_duration.

6) Round Out the Dimension Tables

In this stage, descriptions are created containing information about the dimension tables in the data mart. This is done to help users better understand the data mart.

7) Choose the Durations of the Database

8) The duration used in this study is one year, from August 2023 to August 2024.

8) Determine the Need to Track Slowly Changing Dimensions

As time progresses, dimensions will gradually change. Therefore, this stage determines how to address this issue. There are three ways to handle this:

- Rewrite the changed attributes.
- Create a new record in the dimension.
- Create an alternate attribute to store the new value.

9) Decide the Physical Design

This stage focuses on the physical design of the data mart. The Extract, Transform, Load (ETL) process is carried out at this stage.

3.4. Extract, Transform, Load (ETL)

Extract, Transform, Load (ETL) is the data processing stage from the data source to loading it into the data mart. In this stage, raw data is extracted from various sources, transformed into a format that supports the analysis process, and loaded into the data mart [20]. The ETL process can vary depending on the data available. The result of the ETL process is integrated historical data with a structure that meets business requirements [21]. Below is an explanation of the ETL process [22].

- 1) Extract
- 2) Transform
- 3) Load

The first stage of the ETL process is the extraction of data from various data sources. The data sources used for designing the data mart in this study come from IndoPsyCare's OLTP database, specifically the transaction data. This data resides in the Microsoft SQL Server Management Studio 18 DBMS, which will be connected to the Pentaho Data Integration tool.

The second stage of the ETL process is data transformation, which involves data cleansing. In this stage, the data undergoes normalization, duplicate removal, and sorting. Missing values in the data are also updated to improve the overall quality of the data in the data mart.

The third stage of the ETL process is the loading of data into the data mart. In this stage, the data is organized into an OLAP database, making it ready for use in analysis.

The ETL process is carried out using the Pentaho Data Integration tool and is loaded into the data mart in Microsoft SQL Server Management Studio 18. Once both are connected, further ETL process can begin. It is important to ensure that the database is connected. Below are the stages of the ETL process for the dimension tables: category, client, company, location, provider, and service, using Pentaho Data Integration. Figure 1 illustrates the ETL process for the category dimension. The same steps are followed for the client, company, location, provider, and service dimensions.

- 1) The data source from Microsoft SQL Server Management Studio 18 is extracted using the "Table Input" step. This step is used to retrieve data from the database.
- 2) Once the data has been successfully extracted, data transformation follows. The next step is "Sort Rows," which is used to sort the data.
- 3) The following step is "Unique Rows," which is used to obtain distinct or unique data.
- 4) Next, "Table Input" and "Stream Lookup" steps are used to retrieve the name columns from the master table.
- 5) The next step is "If Field is Null," which is used to find null values in the data. These values are then updated to the desired value.
- 6) The following step is "Add Sequence," which is used to generate surrogate keys for each dimension.
- 7) The next step is "Select Values," which determines the columns to be placed in the dimension table.
- 8) Next, the data resulting from the ETL process is loaded into the relational database using the "Table Output" step. In this case, the data is loaded into Microsoft SQL Server Management Studio 18 as the data mart.
- 9) Finally, the "Execute SQL Script" step is used to execute each line of SQL. In this step, tables in the data mart are created to hold the data resulting from the ETL process. These tables

are created using Data Definition Language (DDL) queries before the data is loaded into the data mart.

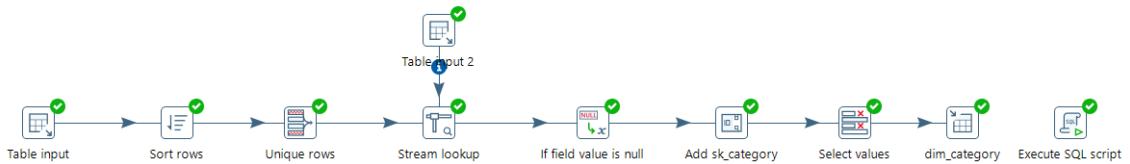


Figure 1. Category Dimension Transformation Steps (Source: Personal Documentation)

The ETL process for the time dimension shares some similarities with other dimension tables. However, in the time dimension, there is an additional step called "Calculator." The Calculator step is used to separate the appointment date in the appointment_date column. Initially, the data is in the format "day - month - year." This data is then split into separate columns for day, month, and year. The ETL process for the time dimension is illustrated in Figure 2.



Figure 2. Time Dimension Transformation Steps (Source: Personal Documentation)

The transaction fact table has a few differences in the ETL process. In the fact table, the **Table Input** and **Stream Lookup** steps are used to retrieve the surrogate key from each dimension table. Next, the **Calculator** step is used for calculations on the total_appointment, total_cancel, and total_duration columns. Additionally, the **Group By** step is used to group the data. The ETL process for the fact table can be seen in Figure 3.

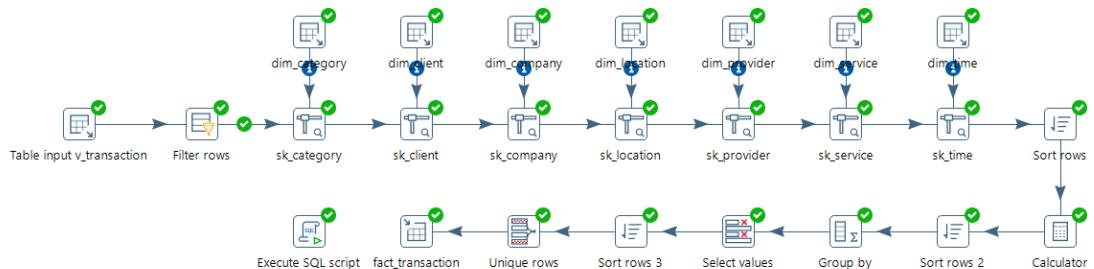


Figure 3. Transaction Fact Transformation Steps (Source: Personal Documentation)

4. Results and Discussion

4.1 Results

This study aims to design a data mart for the transaction business process at IndoPsyCare. To understand the flow of the data mart design process, the researcher has created a data mart architecture.

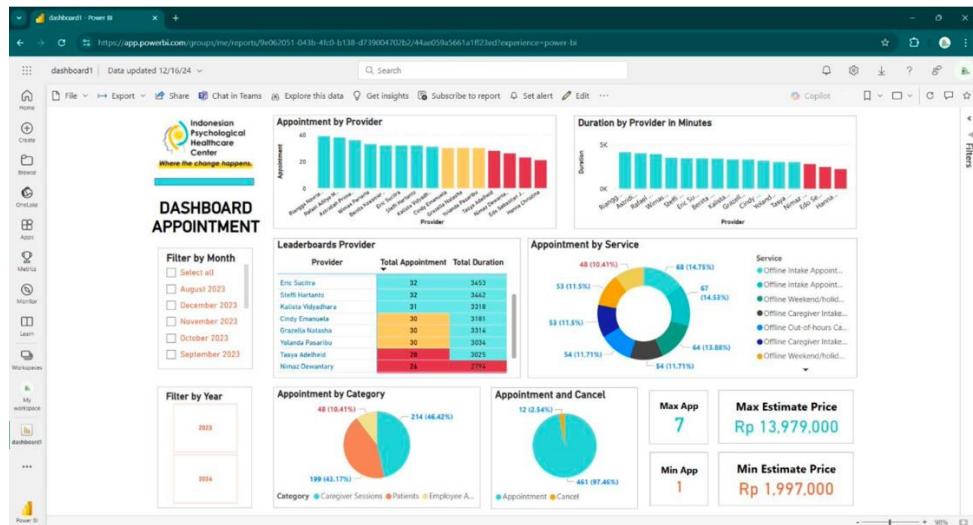


Figure 4. Dashboard Appointment on BI Website (Source: Personal Documentation)

Figure 5 illustrates the architecture of the IndoPsyCare transaction data mart. This architecture depicts the flow of the data mart design process, starting from the data sources used. Next, the ETL process takes place, after which the data is loaded into the data mart. The final stage represents the data analysis phase, where the data has been processed to generate a data mart that presents information in a structured format. The data is analyzed based on the business process needs by the stakeholders of IndoPsyCare.

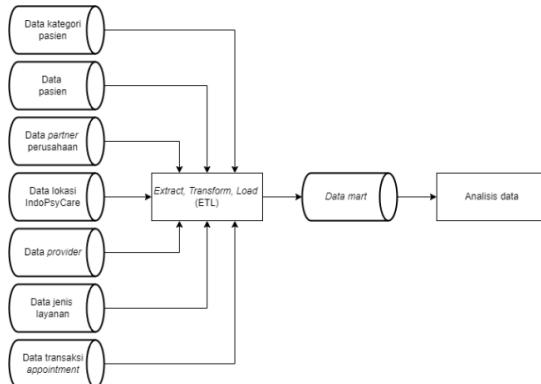


Figure 5. Data Mart Architecture (Source: Personal Documentation)

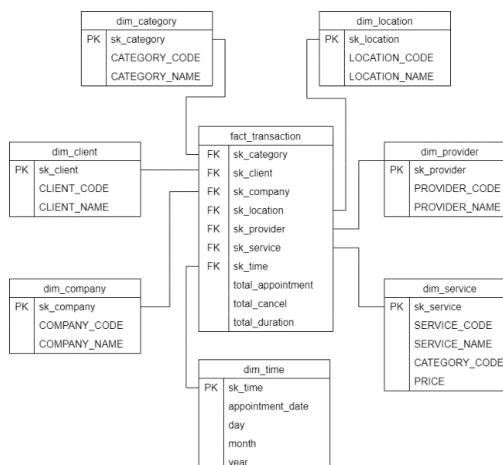


Figure 6. Star Schema (Source: Personal Documentation)

The designed data mart consists of fact tables and dimension tables within the database. The data mart design is depicted using a star schema, which illustrates the relationship between the fact table and dimension tables. The star schema modeling technique can represent multidimensional data [23]. The star schema has the shape of a star, with the fact table at the center, surrounded by dimension tables. The star schema of the data mart designed in this study can be seen in Figure 6.

The fact and dimension tables that have been loaded into the data mart in Microsoft SQL Server Management Studio 18 are shown in Figure 7. With the structured data in the data mart, data retrieval through queries will be faster, thus assisting IndoPsyCare stakeholders during the data analysis process. This has happened because the data has been stored with a focus on a particular business unit, such as appointment. There is a simplification of data making it easier for users to understand the relationship between data [24]. Previously, the data was unstructured and not focused on a particular business unit making it more difficult to understand and analyze. With star schema, users are also easier to create reports and dashboards to monitor KPI.

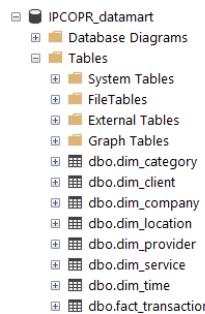


Figure 7. Fact and Dimension Table in Data Mart (Source: Personal Documentation)

4.2 Discussion

The results obtained from the design and implementation of the data mart for IndoPsyCare demonstrate that the proposed model effectively addresses the challenges identified in the Introduction, particularly in transforming transactional OLTP data into an analytical OLAP environment. This structured approach ensures that stakeholders can access reliable information to analyse appointment transactions, monitor service performance, and forecast patient demand.

In comparison to previous studies, this research builds upon and extends the application of Kimball's methodology within healthcare informatics. For instance, Sutanto et al. [1] and Louis et al. [2] emphasised the importance of structured data for business decision-making, but their focus was on retail and pharmaceutical domains rather than mental healthcare. Similarly, Akbar and Rahmanto [3] and Priono et al. [10] demonstrated the Nine-Step method's effectiveness in transforming OLTP data into OLAP structures for sales and export-import data, respectively. The current study adapts these methodological foundations to the mental health sector, addressing a domain-specific need for accurate and accessible analytical data. Furthermore, the findings align with the work of Angela et al. [4] and Finandi et al. [16], who applied OLAP techniques to healthcare services, highlighting the benefits of improved data analysis for operational and clinical decision-making. Delgado et al. [18] reinforced the applicability of Kimball's approach in healthcare business intelligence, yet their studies did not focus on appointment-centric mental health services. By designing a data mart that integrates cost estimation and service-performance indicators within the fact table, this research provides a more domain-specific analytical framework.

The integration of ETL processes, as discussed by Wardhani and Wiratama [24], ensures high-quality, validated data for analysis. Surrogate key management, handling of slowly changing dimensions, and pre-calculation storage mechanisms enhance the robustness of the data mart, echoing principles established in prior studies [12, 14, 17, 21, 22]. Consequently, the current research not only confirms the feasibility of implementing Kimball's methodology in a mental healthcare setting but also contributes to the broader discourse on business intelligence in healthcare, particularly within the Indonesian context.

Results with prior studies, it is evident that the proposed model consolidates and extends existing knowledge. While previous research has demonstrated the general benefits of data marts

and OLAP systems in improving decision support, this study uniquely demonstrates how a structured, appointment-focused data mart can directly impact performance monitoring, cost estimation, and patient service planning. Therefore, the contribution of this research lies in both the methodological adaptation of established data warehousing techniques and the provision of a reproducible, domain-specific model for mental healthcare analytics. Future extensions could explore predictive analytics and real-time data integration, enhancing proactive decision-making and extending the practical applications of this research within healthcare service management.

5. Conclusion

From the data mart design produced in this study, it can be concluded that the data presented is well-structured. The Nine-Step Kimball method has been successfully implemented, involving the Extract, Transform, Load (ETL) process, resulting in a data mart that aligns with the research objectives. The structured data supports fast data retrieval and provides accurate information. This enables IndoPsyCare to analyze data more effectively by utilizing historical OLTP data transformed into OLAP. As a result, it supports IndoPsyCare in the decision-making process to enhance the performance of its services.

The findings of this study underscore the successful design and implementation of a validated data mart that transforms IndoPsyCare's transactional appointment data into a structured analytical repository. Through the application of Kimball's Nine-Step Methodology, integrated with a rigorous ETL process, this research achieved a multidimensional OLAP model that facilitates efficient data retrieval, enhances analytical depth, and ensures decision-quality information for organisational stakeholders. The incorporation of data validation mechanisms such as data type consistency checks, duplicate elimination, referential key alignment, and dimensional integrity verification ensured that only accurate and complete records populated the data mart, thereby strengthening the reliability of subsequent analyses. Beyond technical accuracy, the study demonstrates how well-structured analytical systems can advance mental health service management by enabling performance measurement, demand forecasting, and cost estimation. The research not only affirms the adaptability of the Kimball approach in healthcare informatics but also contributes to the growing discourse on data quality and validation within business intelligence systems in the Indonesian mental health sector. Future work may extend this framework to integrate predictive analytics and real-time data synchronisation, expanding the capacity of IndoPsyCare's data ecosystem toward proactive and precision-driven mental health service delivery.

References

- [1] R. Sutanto, Wasino, and J. T. Beng, "Developing a sales system for Ko Ginhan's special chicken porridge with point of sale system," *AIP Conference Proceedings*, vol. 2680, no. 1, Dec. 2023. [Online]. Available: [/aip/acp/article/2680/1/020061/2928475/Developing-a-sales-system-for-Ko-Ginhan-s-special](https://aip.scitation.org/doi/10.1063/5.0200611). [Accessed: Aug. 30, 2024].
- [2] J. Louis, D. Trisnawarman, and N. J. Perdana, "Perancangan dashboard business intelligence untuk data piutang pada Apotek X," *Jutisi: Jurnal Ilmiah Teknik Informatika dan Sistem Informasi*, vol. 12, no. 3, pp. 1767–1776, 2023.
- [3] M. Akbar and Y. Rahmanto, "Desain data warehouse penjualan menggunakan Nine Step methodology untuk business intelligence," *Jurnal Informatika dan Rekayasa Perangkat Lunak (JATIKA)*, vol. 1, no. 2, pp. 137–146, 2020. [Online]. Available: <http://jim.teknokrat.ac.id/index.php/informatika>.
- [4] O. Angela, R. Nurkholiza, V. Lawrence, D. Trisnawarman, and J. T. Beng, "Rancang bangun dashboard appointment pada layanan kesehatan mental X dengan metode prototyping," *Journal of Information Technology and Computer Science (INTECOMS)*, vol. 7, no. 6, pp. 2011–2020, 2024.
- [5] K. Nisa, D. Sugiarto, and T. Siswanto, "Perancangan data warehouse harga pangan di wilayah Perumda Pasar Jaya," *Jurnal Sistem Informasi dan Telematika (Telekomunikasi, Multimedia dan Informatika)*, vol. 12, no. 1, pp. 47–55, 2021.
- [6] "About IndoPsyCare - Indonesian Psychological Healthcare Center." [Online]. Available: <https://indopsycare.com/about-us/#vm>. [Accessed: Jul. 24, 2024].
- [7] Biro Komunikasi dan Pelayanan Publik KKR, "Menjaga kesehatan mental para penerus bangsa," *Sehat Negeriku*, Oct. 12, 2023. [Online]. Available: <https://sehatnegeriku.id/menjaga-kesehatan-mental-para-penerus-bangsa>.

<https://sehatnegeriku.kemkes.go.id/baca/rilis-media/20231012/3644025/menjaga-kesehatan-mental-para-penerus-bangsa/>. [Accessed: Jul. 24, 2024].

[8] O. K. Sari, N. Ramdhani, and S. Subandi, "Kesehatan mental di era digital: Peluang pengembangan layanan profesional psikolog," *Media Penelitian dan Pengembangan Kesehatan*, vol. 30, no. 4, pp. 337–348, Dec. 2020. [Online]. Available: <https://garuda.kemdikbud.go.id/documents/detail/1996729>. [Accessed: Sep. 3, 2024].

[9] R. J. F. Guanco, L. K. Y. Delgra, U. E. Dotimas, K. B. Dumas, E. R. D. Lumpay, "Mediating role of coping strategies on the symptoms of complicated grief and psychological well-being during COVID-19 pandemic," *Human Behavior, Development and Society*, vol. 24, no. 1, pp. 84–92, Apr. 2023. [Online]. Available: <https://www.researchgate.net/publication/370229603>.

[10] T. R. Priono, W. Purnomo, and N. Y. Setiawan, "Pengembangan data warehouse menggunakan metode Kimball (studi kasus: ekspor & impor fauna dan flora hias air laut)," *Jurnal Pengembangan Teknologi Informasi dan Ilmu Komputer*, vol. 5, no. 8, pp. 3383–3392, 2021. [Online]. Available: <http://j-ptik.ub.ac.id>.

[11] R. M. Stair and G. W. Reynolds, *Principles of Information Systems*. Boston, MA, USA: Cengage Learning, 2018.

[12] A. K. Hamoud, M. K. Hussein, Z. Alhilfi, and R. H. Sabr, "Implementing data-driven decision support system based on independent educational data mart," *International Journal of Electrical and Computer Engineering*, vol. 11, no. 6, pp. 5301–5314, Dec. 2021.

[13] V. Banja, M. Ilić, L. Kopanja, D. Zlatković, M. Trajković, and D. Ćurguz, "Microsoft SQL Server and Oracle: Comparative performance analysis," in *Proc. 7th Int. Conf. Knowledge Management and Informatics*, 2021, pp. 33–40.

[14] N. Leite, I. Pedrosa, and J. Bernardino, "Open source business intelligence on a SME: A case study using Pentaho," in *Proc. 14th Iberian Conf. Information Systems and Technologies (CISTI)*, Coimbra, Portugal, 2019, pp. 1–7.

[15] Charlie, J. T. Beng, and D. Arisandi, "Website-based information system for mapping restaurants or eating places in DKI Jakarta using Google Maps," *IOP Conference Series: Materials Science and Engineering*, vol. 1007, no. 1, Dec. 2020. [Online]. Available: <https://iopscience.iop.org/article/10.1088/1757-899X/1007/1/012157>. [Accessed: Aug. 30, 2024].

[16] M. J. Finandi, Fauziah, and I. D. Sholihat, "Sistem informasi pendataan pelayanan kesehatan penderita diabetes mellitus menggunakan metode Online Analytical Processing (OLAP)," *KLIK: Kajian Ilmiah Informatika dan Komputer*, vol. 4, no. 1, pp. 53–61, 2023.

[17] D. Sihombing, "Academic data warehouse modeling in higher education using Nine-Step design methodology," *Journal of Information Systems and Informatics*, vol. 4, no. 4, pp. 1126–1134, Dec. 2022. [Online]. Available: <https://www.journal-isi.org/index.php/isi/article/view/399>.

[18] A. Delgado, F. Rosas, and C. Carbajal, "System of business intelligence in a health organization using the Kimball methodology," in *2019 IEEE Chilean Conf. Electrical, Electronics Engineering, Information and Communication Technologies (CHILECON)*, 2019, pp. 1–5.

[19] S. Anshari and S. Retno, "Penerapan metode Nine-Step Kimball dalam pengolahan data history menggunakan data warehouse dan business intelligence," *Jurnal Ilmu Komputer*, vol. 16, pp. 69–79, Sep. 2023.

[20] M. Madhikerrni and K. Främling, "Data discovery method for extract-transform-load," in *2019 IEEE 10th Int. Conf. Mechanical and Intelligent Manufacturing Technologies (ICMIMT)*, 2019, pp. 205–212.

[21] N. Biswas, A. Sarkar, and K. C. Mondal, "Efficient incremental loading in ETL processing for real-time data integration," *Innovations in Systems and Software Engineering*, vol. 16, no. 1, pp. 53–61, 2020. [Online]. Available: <https://doi.org/10.1007/s11334-019-00344-4>.

[22] M. Venkateswarlu and T. G. Vasista, "Extraction, transformation and loading process in the cloud computing scenario," *International Journal of Engineering Applied Sciences and Technology*, vol. 8, no. 1, pp. 232–236, 2023.

[23] R. Saputra and D. Trisnawarman, "Perancangan dashboard inventory e-commerce Anicca menggunakan Microsoft Power BI," *Jutisi: Jurnal Ilmiah Teknik Informatika dan Sistem Informasi*, vol. 12, no. 3, pp. 1475–1483, 2023.

[24] F. Z. D. Wardhani and J. Wiratama, "Improving the quality of service: ETL implementation on data warehouse at pharmacy industry," *Jurnal Tekno Kompak*, vol. 18, no. 1, pp. 1–14, Feb. 2024, doi: 10.33365/JTK.V18I1.3211.