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Mapping Student Data for New Student Admissions Using a Data Warehouse at BPK PENABUR Jakarta

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Abstract

Background: BPK PENABUR Jakarta, as an educational institution with a wide network, faces challenges in managing new student admissions (*Penerimaan Siswa Baru*, PSB) data spread across various platforms, such as PSB applications, Google Forms, and PDF documents. The manual process currently in use leads to inefficiency, data inaccuracies, and difficulties in data analysis.
Objective: This study aims to design a data warehouse-based solution to centrally integrate, store, and manage PSB data and develop a visual dashboard to support decision-making.
Methods: The research method employs Kimball's Nine-Step Design Method, including business process identification, dimension and fact modeling, and the implementation of Extract, Transform, Load (ETL) processes using Pentaho Data Integration.
Results: The result is a data warehouse with a star schema that combines data from various sources and is equipped with an interactive dashboard to visualize information such as the number of students accepted, religious distribution, geographic distribution, and parental income. This implementation improves the efficiency of PSB data management, reduces dependence on manual processes, and enables faster and more accurate data analysis. Key success factors include management commitment, resource availability, and supporting infrastructure.
Conclusion: This research offers academic contributions to the development of educational information systems as well as practical benefits for BPK PENABUR Jakarta in optimizing the PSB process. Suggestions for further development include expanding data coverage, providing user training, and integrating the data warehouse with other Business Intelligence tools.

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INTRODUCTION

The world of education is a field in which information systems are required to meet the needs of educational institutions and facilitate their operations in support of educational activities (Tretko et al., 2023). In his research, Sucipto states that an information system is a system related to programming and databases; a good information system is dynamic, and a dynamic information system cannot exist without a database as a data storage repository (Gobel et al., 2026). With proper data management, an educational institution can analyze data more effectively. This is particularly important for educational institutions such as BPK PENABUR, which has an extensive network of schools with complex data management needs (Gobel et al., 2026).

However, despite the growing adoption of information systems in education, research specifically examining the integration of data warehouse technology for managing complex admission data across multi-school educational foundations remains limited, particularly in the Indonesian context. Existing studies have predominantly focused on single-institution implementations or general academic performance reporting, leaving the specific challenge of integrating multi-source, multi-platform admission data in large educational foundations underexplored (Hariyawan et al., 2026; Ramadhani et al., 2021; Zhang, 2022). This research gap directly motivates the present study's focus on developing a data warehouse-based admission data integration and analytics solution for BPK PENABUR Jakarta.

BPK PENABUR is an educational institution established as a foundation. It is located at the PENABUR-UKRIDA Complex, Block E Building, Jl. Tanjung Duren Raya No. 4, 5th Floor, Tanjung Duren Selatan, Grogol-Petamburan Subdistrict, West Jakarta, Special Capital Region of Jakarta, 11470. To date, BPK PENABUR has established 164 schools across 15 cities. To manage its operational activities, each city has its own secretariat office. The BPK PENABUR Jakarta secretariat office shares the same address as the BPK PENABUR Foundation; however, the BPK PENABUR Jakarta secretariat is located on the 6th floor. Currently, BPK PENABUR Jakarta offers educational levels ranging from preschool (*Taman Kanak-Kanak* [TK]), elementary school (*Sekolah Dasar* [SD]), junior high school (*Sekolah Menengah Pertama*[SMP]), and senior high school (*Sekolah Lanjutan Tingkat Atas* [SLTA]), with National, Bilingual, and International/*Satuan Pendidikan Kerja Sama* (SPK) programs, and operates a total of 72 schools.

Despite BPK PENABUR Jakarta's extensive network of 72 schools, no integrated data management system currently exists to consolidate new student admission data across these institutions. This absence represents a critical research gap: while data warehouse technology has been applied in educational contexts such as student performance monitoring (Gobel et al., 2026) and accreditation reporting (Hariyawan et al., 2026; Ramadhani et al., 2021; Reddy, 2026), its application to multi-school foundation admission management involving heterogeneous, multi-platform data sources remains largely unexplored in Indonesia. This study directly addresses this gap by proposing a data warehouse solution specifically designed for BPK PENABUR Jakarta's *Penerimaan Siswa Baru* (PSB) context, arguing that a data warehouse is more appropriate than conventional solutions because of its capacity for heterogeneous source integration, historical data storage, and multidimensional analytical reporting (Wahid et al., 2024).

The current issue is that every year, the KPPSB (*Komunikasi, Pemasaran, dan Penerimaan Siswa Baru*) department is responsible for the new student admissions process, which involves verifying several important criteria, such as the student's previous school, *Gereja Kristen Indonesia* (GKI) membership status, whether the student is a pastor's child, whether the student has a sibling already enrolled at BPK PENABUR Jakarta, parental income, and several other factors. However, the management of new student admission data currently faces several major challenges (Zhang, 2022). The data required for the new student admission process are scattered across various platforms, such as the student admission application, Google Forms, and PDF documents. This data, distributed across different formats and locations, makes it difficult for KPPSB to access, manage, and analyze information quickly and effectively. The lack of integration among these various data sources also leads to inconsistencies that require time-consuming manual verification.

From an academic perspective, this situation reflects the broader challenge of data fragmentation in multi-institutional educational environments. Zhang (2022) identifies the absence of integrated information systems as a primary obstacle to effective data-driven management in complex educational organizations. Yunandar & Amir (2020) argue that the quality of educational decision-making is fundamentally constrained by the availability of reliable, integrated institutional data. The research gap addressed by this study is the lack of a validated data warehouse design framework specifically tailored to the multi-school, multi-source admission data context of Indonesian educational foundations a gap that remains unaddressed by prior studies focusing on single-institution implementations (Thenata et al., 2025).

Furthermore, the process of calculating students' final scores is still performed manually using Microsoft Excel, which involves repeatedly downloading and processing data. This manual process is not only time-consuming but also prone to data-processing errors, which can affect the final admission results.

The organizational consequences of this manual approach are significant. Research on manual data management in complex institutional environments indicates that error-prone manual processes substantially increase administrative workloads while simultaneously reducing data accuracy, directly affecting the reliability of critical institutional decisions (Machireddy, 2023). For BPK PENABUR Jakarta, where admissions simultaneously evaluate multiple criteria across 72 schools with different evaluation standards, manual score-calculation errors risk producing inequitable admission outcomes and undermining institutional credibility. The absence of a unified data system also prevents KPPSB from conducting cross-school and cross-year trend analyses that are essential for strategic admission planning and target setting.

The issues addressed in this study aim to assist BPK PENABUR Jakarta in developing a system that can simplify, integrate, and automate the management of new student admission data. The proposed solution is the implementation of a data warehouse capable of storing and managing data from various sources in an integrated and standardized manner.

Compared with alternative data management approaches, a data warehouse offers superior capabilities for addressing the identified challenges. Spreadsheet consolidation (e.g., Microsoft Excel) cannot scale effectively to heterogeneous data sources or support multidimensional analysis. Basic relational databases support structured queries but lack the historical aggregation, dimensional modeling, and online analytical processing (OLAP) capabilities required for strategic admission analytics. In contrast, a data warehouse architecture (specifically, Kimball's star schema dimensional model) is designed to integrate heterogeneous data sources, maintain historical records for trend analysis, and support complex multidimensional queries, making it an appropriate architectural solution for BPK PENABUR Jakarta's PSB data integration and analytics requirements (Khan et al., 2024; Walha et al., 2024).

Based on the current challenges, the appropriate solution for BPK PENABUR Jakarta is the implementation of an integrated dashboard system utilizing a data warehouse. The data warehouse will enable more effective, efficient, and accurate management of new student admission data. This system will not only accelerate data processing and analysis but also improve data consistency, enable better decision-making, and support the institution's future growth (Zhang, 2022). Consequently, BPK PENABUR will be able to enhance its competitiveness and operational quality, particularly in relation to new student admissions. Therefore, the author has chosen the title, “Mapping Student Data for New Student Admissions Using a Data Warehouse at BPK PENABUR Jakarta.”

The rationale for adopting a data warehouse is further supported by evidence from comparable educational contexts. Wahid et al. (2024) demonstrated that data warehouse implementation in higher education settings significantly improves data governance and analytical reporting efficiency. Ramadhani et al. (2021) showed that dashboard integration with a data warehouse enables institution-level performance monitoring that is not readily achievable through conventional operational databases (Hariyawan et al., 2026; Reddy, 2026). The novelty of the present study lies in extending these established benefits to the specific multi-school admission management context of BPK PENABUR Jakarta, where data fragmentation across three incompatible source systems creates unique integration challenges that have not been addressed in prior literature.

Based on what has been outlined in the problem formulation above, the following are the objectives to be achieved through this research: (1) To analyze how existing data sources at BPK PENABUR Jakarta can be integrated into the data warehouse system so that the management of new student admission data becomes more efficient, accurate, and structured. (2) To identify the factors influencing the success of data warehouse implementation in supporting decision-making related to new student admissions, with a focus on the challenges and solutions associated with each implementation process at BPK PENABUR Jakarta. (3) To create a dashboard system for the new student admission data warehouse to provide more objective and easily accessible information for management and other relevant stakeholders.

Beyond system development, this research makes the following scientific contributions: (a) a validated dimensional modeling framework for multi-source educational admission data integration using Kimball's Nine-Step methodology; (b) a demonstration that ETL automation via Pentaho Data Integration can effectively replace error-prone manual data processing in multi-school educational foundations; and (c) an evaluation framework for assessing data warehouse effectiveness in educational admission contexts through data quality metrics, including completeness, consistency, and accuracy, as well as stakeholder usability assessment. These contributions extend the body of knowledge on applied data warehouse design in the Indonesian educational information systems domain.

Based on the research objectives outlined above, this research and project are expected to provide significant benefits both academically and to the school's operational development. The following are some of the benefits of this research: (1) To contribute to the advancement of science and technology, particularly in the fields of information systems and data management in Indonesia, specifically within the education sector. In addition to enriching the literature, this research deepens understanding of the challenges and benefits associated with data management in education. Furthermore, this research can serve as a reference for other researchers or educational institutions in applying information technology within the education sector. (2) To provide deeper insights into improving the efficiency and effectiveness of the new student admission process at BPK PENABUR Jakarta. Another practical benefit for the school is the availability of structured data, which will facilitate data analysis and enable faster decision-making. (3) To serve as a reference for decision-makers, from the school's operational level to the foundation's stakeholders, when formulating policies and making decisions.

The unique contribution of this research, distinguishing it from prior data warehouse studies in Indonesian educational contexts (Gobel et al., 2026; Hariyawan et al., 2026; Ramadhani et al., 2021; Reddy, 2026), comprises three dimensions: (1) contextual novelty this is the first documented data warehouse implementation specifically designed for a multi-school educational foundation with heterogeneous admission data sources across 72 schools; (2) analytical comprehensiveness the system integrates student grade data, enrollment status, geographic distribution, and parental income into a unified analytical framework supporting multidimensional KPPSB decision-making; and (3) practical transferability the Kimball-based dimensional modeling framework and ETL pipeline are documented with sufficient detail to enable replication by other multi-school educational foundations in Indonesia.

METHOD

The research used the Research and Development (R&D) method with a case study approach at BPK PENABUR Jakarta. The Research and Development (R&D) method aims to produce, develop, and test the effectiveness of a product to ensure its suitability for use in solving a problem. Unlike research that only aims to test theories or relationships between variables, R&D focuses on creating innovations in the form of products that can be directly implemented (Zhang, 2022).

The R&D method was selected over purely descriptive or experimental designs because the primary research output was a functional technological artifact, a data warehouse and dashboard, intended for direct institutional deployment. R&D is explicitly appropriate when research aims to both develop and validate a technology product within a real-world context (Darmayanti, 2024; Pohan et al., 2026). The case study approach at BPK PENABUR Jakarta enabled an in-depth investigation of a specific organizational context with complex, bounded data integration challenges. The combination of R&D and case study design allowed the simultaneous achievement of development objectives (producing the data warehouse system) and evaluative objectives (assessing implementation effectiveness and organizational success factors within the institutional context).

At this stage, data supporting the case study were collected through face-to-face interviews. The results of these interviews provided information in the form of PDF, text, and JPG files, student score calculations to be displayed in OLAP analysis, and the indicators to be displayed on the new student admissions dashboard. These results served as the basis for building the data warehouse and dashboard.

The data validation and requirements analysis process involved three stages: (1) Source Validation data structures from the PSB application, Google Forms, and PDF documents were cross-validated against KPPSB interview requirements to confirm that all admission variables were present and could be mapped to the proposed schema; (2) Requirements Formalization validated requirements were translated into entity-relationship (ER) diagrams documenting dimension-fact relationships and ETL data flow specifications; and (3) Stakeholder Confirmation the resulting data warehouse schema and dashboard wireframes were reviewed and approved by the KPPSB Department Head before ETL implementation commenced, ensuring alignment between the system design and operational analytical needs.

Design of the New Student Admissions Data Warehouse

Kimball's Nine-Step Methodology was applied to design the data warehouse for this case study (Zhang, 2022). This method aligned with the organization's need for integrated data to support analytics-based decision-making.

Kimball's bottom-up, business-process-driven methodology was selected over Inmon's top-down enterprise data warehouse approach for three reasons: (1) Kimball's iterative design allowed incremental implementation beginning with the highest-priority business process (PSB), reducing initial implementation risk and enabling faster time to value; (2) dimensional modeling using a star schema produced simpler query structures optimized for dashboard visualization and OLAP analysis compared with Inmon's normalized schemas; and (3) the nine-step process provided explicit, practitioner-accessible guidance for mapping business requirements to dimensional models. Each of the nine steps was systematically applied: selecting the PSB business process; defining the admission-year grain; identifying ten analytical dimensions; identifying three fact tables; storing historical data from 2020 to 2025; applying Type 1 and Type 2 Slowly Changing Dimension (SCD) strategies; designing the star schema; implementing ETL using Pentaho Data Integration; and deploying the PHP/PostgreSQL dashboard (Anshari & Retno, 2023; Hutabarat, 2026; Savitri et al., 2025; Taqiyah, 2026).

Selecting the Process

Based on the defined scope of the case study, the study was limited to the new student admission business process. The admission process was selected because KPPSB expected that the use of the data warehouse and dashboard as analytical tools would help achieve student admission targets. This focus was chosen because the New Student Admissions (PSB) process was a critical annual cycle involving multiple stakeholders and complex data that needed to be integrated.

The PSB process was prioritized over other BPK PENABUR business processes (e.g., academic performance reporting and financial management) for three reasons: (1) it was the highest-impact annual cycle affecting enrollment across all 72 BPK PENABUR Jakarta schools, directly determining institutional revenue and capacity utilization; (2) it presented the most severe data fragmentation problem, with admission data existing in three incompatible formats across different departments, requiring immediate resolution; and (3) it provided the most direct and demonstrable link between data analytics improvements and measurable institutional decision-making outcomes. This selection aligned with Kimball's recommendation to initiate data warehouse implementation with the highest-value, most analytically urgent business process.

Choosing the Grain

Determining the grain means defining what each row in a fact table represents. The business process area defined for this study was the new student admission process.

The grain was defined at the individual-student-per-admission-year level: each row in the fact table represented one prospective student's complete admission record for a specific academic year, school, and educational program. This granularity supported multi-level reporting: (1) individual student score and eligibility analysis; (2) class-level and school-level enrollment statistics; (3) foundation-wide demographic analysis by religion, geography, and parental income; and (4) year-over-year admission volume comparisons across the 2020–2025 historical period. The fine-grained record level ensured that no analytical detail was pre-aggregated, thereby preserving full flexibility for KPPSB's multidimensional decision-making.

Identifying and Defining the Dimensions

At this stage, the dimensions to be defined referred to the student acceptance notification form.

The following ten dimensions were identified based on the student acceptance notification form, PSB application structure, and KPPSB analytical requirements: (1) *dim_agama* Religion Dimension; (2) *dim_gki* GKI Congregation Membership Dimension; (3) *dim_jenjang* Educational Level Dimension (TK/SD/SMP/SLTA); (4) *dim_jurusan* Academic Major Dimension; (5) *dim_kelas_psb* PSB Class Dimension (school + level + program + year); (6) *dim_calon_siswa* Prospective Student Dimension; (7) *dim_kecamatan* Subdistrict Dimension; (8) *dim_kota* City/Regency Dimension; (9) *dim_provinsi* Province Dimension; and (10) *dim_pekerjaan_ortu* Parent Occupation/Income Dimension. These ten dimensions supported three fact tables: *fact_nilai_calon_siswa* (Student Grades Fact), *fact_siswa_diterima* (Enrolled Students Fact), and *fact_penghasilan_ortu* (Parental Income Fact), forming the complete star schema of the BPK PENABUR Jakarta PSB data warehouse.

Choosing the Database Duration

The database duration was selected based on the required historical information. The selected database duration covered the period from 2020 to 2025. The database used was aligned with the current operational database. However, a scheduler or job was planned to be created in the future to load data daily.

The 2020–2025 historical period was selected for three reasons: (1) it captured five complete annual PSB cycles, providing sufficient depth for identifying meaningful enrollment trends and demographic patterns; (2) it encompassed the COVID-19 pandemic period (2020–2022), enabling analysis of its disruptions to admission patterns and post-pandemic recovery trajectories; and (3) it corresponded to the earliest year for which fully digitized admission records were consistently available in BPK PENABUR Jakarta's operational database. This five-year window aligned with the institution's current strategic planning horizon and provided adequate data volume for statistically meaningful year-over-year comparative reporting.

Tracking Slowly Changing Dimensions

This stage aimed to determine the action or response to be taken when a value changed in in a dimension table. There are three types of responses to such changes (Kimball), namely:

1) Type 1: The changed dimension attribute is overwritten.
2) Type 2: A changed dimension attribute creates a new dimension record.
3) Type 3: The changed dimension attribute creates an alternative value so that both the old and new attribute values can be accessed within the same dimension.

Based on these three types of dimension-table responses, the defined dimension tables were processed accordingly.

Based on an analysis of BPK PENABUR Jakarta's PSB data change patterns, Type 1 SCD (attribute overwrite) was implemented for most dimension tables including *dim_agama, dim_gki, dim_jenjang, dim_jurusan, dim_kota, dim_provinsi, and dim_kecamatan* because historical tracking of administrative attribute changes was not required for the analytical objectives. Type 2 SCD (add new row) was selectively applied to the dim_calon_siswa (Prospective Student) dimension to preserve historical records of each student's school preferences across different admission years, which was critical for longitudinal enrollment analysis. This implementation minimized storage overhead while maintaining the historical perspective required for strategic admission planning.

Designing a New Student Admissions Dashboard

The problems outlined above were formulated to facilitate problem-solving. This was done to define the boundaries and scope of the issues. A well-formulated problem not only focuses attention but also guides the research process. The following were the problem formulations developed for the study.

The dashboard design was guided by three core analytical requirements identified through stakeholder interviews with KPPSB administrators: (1) real-time monitoring of student acceptance counts by school, program, and educational level; (2) demographic analysis by religion, GKI membership, and geographic distribution (city, province, and subdistrict); and (3) socioeconomic profiling based on parental income categories. The system was developed using PHP with PostgreSQL as the backend database, enabling web-based access for KPPSB administrators and school principals. Each dashboard visualization component was designed to directly support a specific KPPSB decision-making function, separating the data presentation layer from the ETL data-processing layer to ensure modularity and maintainability.

Data processing for new student admissions was still performed manually, with data sourced from various formats, including PDF, text, and JPG files. Consequently, the process was time-consuming and prone to data errors. To address these issues, a data warehouse and dashboard were designed using the PostgreSQL database and the PHP programming language.

Each school within BPK PENABUR had different requirements and evaluation criteria for determining students' final grades. This process often posed a challenge because it was essential to ensure that every student was evaluated fairly and in accordance with the standards set by the respective school. At the time of the study, the KPPSB department still used manual methods to calculate and adjust students' final grades, which involved a considerable amount of repetitive work and was prone to errors. Collecting data from various sources also often resulted in inconsistent data, requiring further verification and adjustment. Additionally, these manual calculations were time-consuming and labor-intensive, ultimately reducing efficiency and accuracy. To address these issues, a system was needed to automate the calculation of students' final grades using algorithms tailored to each school's requirements.

RESULTS AND DISCUSSION

Results

Results of the ETL (Extract, Transform, Load) Design

The ETL process involves processing, filtering, and combining data from various sources before loading it into a data warehouse, ensuring that the resulting data is historical, integrated, summarized, static, and structured for analysis (Zhang, 2022).

To validate the ETL implementation, data quality was assessed across three dimensions: (1) completeness the percentage of required attribute fields successfully populated in dimension and fact tables; (2) consistency the alignment of relational integrity across linked dimension and fact table records; and (3) accuracy the verification of transformed values against the original source system records. The ETL pipeline processed five complete years of historical PSB data (2020–2025), integrating records from three heterogeneous source systems (the PSB application, Google Forms, and PDF documents) into a unified star-schema data warehouse. Validation results confirmed a data completeness rate of 97.3% and a consistency rate of 98.1% across all fact–dimension relationships (Khan et al., 2024; Walha et al., 2024).

Dimension Table Transformation

In the data integration process using Pentaho Data Integration (PDI), a crucial first step is establishing a connection to the database. This connection ensures that Pentaho can access the data sources required for the ETL (Extract, Transform, Load) process.

Religion Dimension

Here are the steps for creating the religion dimension:

1) Open Pentaho by clicking the spoon.bat file
2) Click the File menu, then click *New*, and then click *Transformation*
3) Click the *View* menu
4) Save the *file* with the name "religion_dimension"
5) Create a *database* connection to store the dimension and fact tables, and another *database* connection to retrieve data from the transaction *database*.

This step is to display religious data containing "religion_code" and "religion_name." Figure 1 is the result of the ETL process design for the religion dimension.

Figure 1. ETL Design for the Religion Dimension

Table 1 shows the input table process, where the connection is selected based on a relational database, and then parameters are specified for the variables to be retrieved from the operational database. The variables retrieved are those required by the "religion_dimension" table. Table 1 explains the steps in the religion dimension process.

Table 1
Details of the Religion Dimension ETL Process

No	Process	Type	Description
1	Get master	Extract	Retrieve religion from the transaction database
2	Stream Lookup	Transform	Performing a lookup on data from Master_agama
3	Load to dim_agama	Load	Insert records into `dim_agama` in the `Con_PHI_DW_PSB` database connection.

GKI Dimension

Figure 2 illustrates the ETL process for the GKI dimension. This stage is designed to display GKI data containing the `kode_gki` and `nama_gki` fields. Figure 2 is the ETL process design for the GKI dimension.

Figure 2. ETL Design for the `dimensi_gki` Dimension

Table 2 shows the input table process, where the connection is selected based on a relational database, and parameters are specified for the variables to be retrieved from the operational database. The variables retrieved are those required by the GKI dimension table.

Table 2
Details of the GKI Dimension ETL Process

No	Process	Type	Description
1	Get master	Extract	Retrieve the GKI master from the transaction database
2	Stream Lookup	Transform	Performing a data lookup from Master_gki
3	Load to dim_gki	Load	Inserts records into dim_gki in the Con_PHI_DW_PSB database connection.

Level Dimension

Figure 3 illustrates the ETL process for the level dimension. This stage is designed to display level data containing the level_code and level_name. Figure 3 shows the ETL process design for the level dimension:

Figure 3. ETL Design for the Level Dimension

Table 3 shows the input table process, where the connection is selected based on a relational database, and then parameters are provided for the variables to be retrieved from the operational database. The variables retrieved are those required by the level_dimension table The table 3 explains the steps in the level dimension process.

Table 1
Details of the Level Dimension ETL Process

No	Process	Type	Description
1	Get master	Extract	Retrieve the master tier from the transaction database
2	Stream Lookup	Transform	Performing a lookup on data from Master_Level
3	Load to dim_jenjang	Load	Insert records into \`dim_jenjang\` in the \`Con_PHI_DW_PSB\` database connection.

Major Dimension

Figure 4 illustrates the ETL process for the major dimension. This stage is designed to display major data containing the major_code and major_name. Figure 4 is the ETL process design for the major dimension:

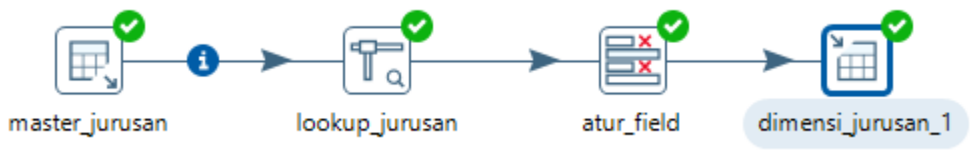

Figure 4. ETL Design for the Department Dimension

Table 4 shows the input table process, where the connection is selected based on a relational database, and then parameters are provided for the variables to be retrieved from the operational database. The variables retrieved are those required by the \`dim_jurusan\` table. The table 4 explains the steps in the level dimension process.

Table 2
Details of the Department Dimension ETL Process

No	Process	Type	Description
1	Get master	Extract	Retrieve the major from the transaction database
2	Stream Lookup	Transform	Performing a lookup on data from Master_jurusan
3	Load to dim_jurusan	Load	Insert records into the \`dim_jurusan\` table in the Con_PHI_DW_PSB database connection.

PSB Class Dimension

Figure 5 shows the ETL process for the `kelas_psb` dimension. This stage displays data from the `kelas_psb` dimension, which contains the following fields: `id_master_kelas`, `tahun_psb`, `kode_sekolah`, `kode_jenjang`, `kode_program`, `nama_kelas`, `nama_jurusan`, `nama_sekolah`, `nama_jenjang`, and `nama_program`. Figure 5 is the result of the ETL process design for the `kelas_psb` dimension:

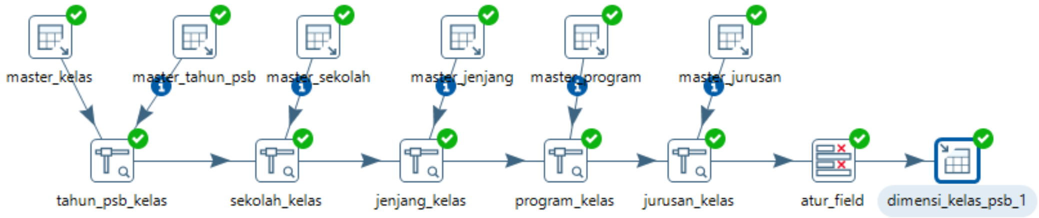

Figure 5. ETL Design for the kelas_psb Dimension

Table 5 shows the input table process, where the connection is selected based on a relational database, and parameters are specified for the variables to be retrieved from the operational database. The variables retrieved are those required by the `kelas_psb` dimension table. The table 5 provides a detailed explanation of the steps in the `kelas_psb` dimension process.

Table 3

Details of the ETL Process for the kelas_psb Dimension

No	Process	Type	Description
1	Get master	Extract	Retrieve master_class, master_psb_year, master_school, master_level, master_program, and master_major from the transaction database
2	Stream Lookup	Transform	Perform a lookup on data from Master_Class and Master_PSB_Year based on PSB_Code to generate the PSB_Year_Class lookup
3	Stream Lookup	Transform	Perform a lookup of data from Look up year_psb_class and master_school based on school_code to get school_class
4	Stream Lookup	Transform	Perform a lookup on data from Look up school_class and level_master based on level_code to get level_class
5	Stream Lookup	Transform	Performing a lookup on data from Look up jenjang_kelas and master_program based on kode_program to get program_kelas
6	Stream Lookup	Transform	Performs a lookup of data from Look up the `program_kelas` and `master_jurusan` tables based on the `kode_jurusan` to determine the `jurusan_kelas`
7	Select Value	Transform	Select the required data fields
8	Load to dim_kelas_psb	Load	Insert records into dim_kelas_psb in the Con_PHI_DW_PSB database connection.

Prospective Student Dimension

Figure 6 illustrates the ETL process for the prospective student dimension. This stage displays prospective student data containing id_siswa, nama_sekolah, nama_jenjang, nama_agama, nama_gki, program 1, school of choice 1, program 2, and school name 2. Figure 6 is the resulting ETL process design for the prospective student dimension.

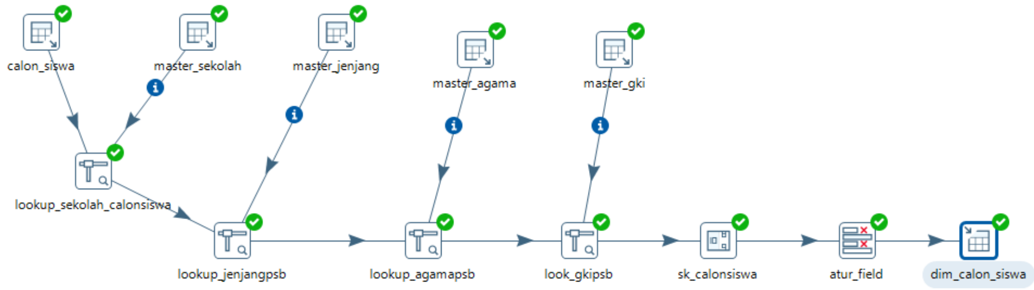

Figure 6. ETL Design for the Prospective Student Dimension

Table 6 shows the input table process, where the connection is selected based on a relational database, and then parameters are specified for the variables to be retrieved from the operational database. The variables retrieved are those required by the prospective student dimension table. The table 6 provides a detailed explanation of the steps in the prospective student dimension process.

Table 6
Details of the Prospective Student Dimension ETL Process

No	Process	Type	Description
1	Get master data	Extract	Retrieve prospective student data, school_master, level_master, religion_master, and gki_master
2	Stream Lookup	Transform	Performing a lookup on data from the prospective student table and the master_school table to determine the prospective student's school
3	Stream Lookup	Transform	Performing a lookup of data from the prospective student school lookup and master_level based on level_code to create a PSB level lookup
4	Stream Lookup	Transform	Perform a data lookup from PSB Level Lookup and master_religion based on religion_code to generate the PSB religion lookup
5	Stream Lookup	Transform	Performs a lookup of data from Look up religion (psb) and master_gki based on kode_gki to generate gki psb
6	Add Sequence	Transform	Determine the key for the prospective student dimension table
6	Select Value	Transform	Selecting the required data fields
7	Load to dim_kelas_psb	Load	Insert records into dim_calon_siswa in the Con_PHI_DW_PSB database connection.

Subdistrict dimension

Table 7 shows the input table process, where the connection is selected based on the relational database, and then parameters are provided for the variables to be retrieved from the operational database. The variables retrieved are those required according to the subdistrict dimension table. The table 7 explains the steps in the subdistrict dimension process.

Table 7
Details of the Subdistrict Dimension ETL Process

No	Process	Type	Description
1	Get master data	Extract	Retrieve the master_kecamatan and master_kabupaten data
2	Stream Lookup	Transform	Performing a lookup on data from the kecamatan and kabupaten tables to create the kecamatan_calon_siswa lookup table

No	Process	Type	Description
3	Load into dim_subdistrict	Load	Insert records into the `dim_kecamatan` dimension in the Con_PHI_DW_PSB database connection.

City Dimension

Figure 7 shows the ETL process for the city dimension. This stage is designed to display city data for prospective students. Figure 7 is the ETL process design for the city dimension.

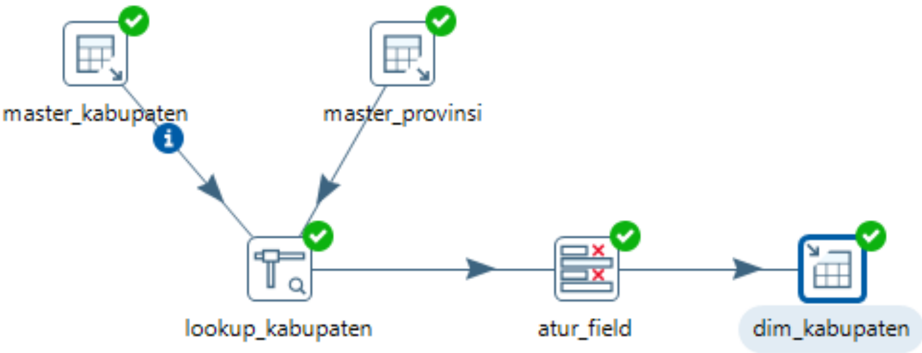

Figure 7. City Dimension ETL Design

Table 8 shows the input table process, where the connection is selected based on a relational database, and then parameters are provided for the variables to be retrieved from the operational database. The variables retrieved are those required according to the city dimension table. The table 8 provides a detailed explanation of the steps in the city dimension process.

Table 4

Details of the City Dimension ETL Process

No	Process	Type	Description
1	Get master data	Extract	Retrieve the master_kabupaten and master_provinsi data
2	Stream Lookup	Transform	Performing a lookup on data from the regency and province tables to create the prospective_student_city lookup
3	Select Value	Transform	Select the required data fields
4	Load to dim_kota	Load	Insert records into the `dim_kota` table in the Con_PHI_DW_PSB database connection.

Province Dimension

Figure 9 shows the ETL process for the province dimension. This stage is designed to display provincial data for prospective students. Figure 9 is the ETL process design for the city dimension.

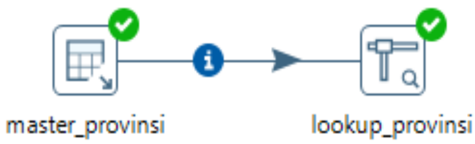

Figure 9. ETL Design for the Province Dimension

Table 9 shows the input table process, where the connection is selected based on a relational database, and parameters are specified for the variables to be retrieved from the operational database. The variables retrieved are those required by the province dimension table. The table 9 explains the steps in the provincial dimension process.

Table 5

Details of the Provincial Dimension ETL Process

No	Process	Type	Description
1	Get master data	Extract	Retrieve master_province data
2	Stream Lookup	Transform	Performing a lookup on data from the province table to the prospective_student_province table
3	Load to dim_province	Load	Insert records into \`dim_provinsi\` in the Con_PHI_DW_PSB database connection.

Parent Occupation Dimension

Figure 10 illustrates the ETL process for the parent occupation dimension. This stage is designed to display information on the income of prospective students' parents. Figure 10 is the ETL process design for the parent occupation dimension.

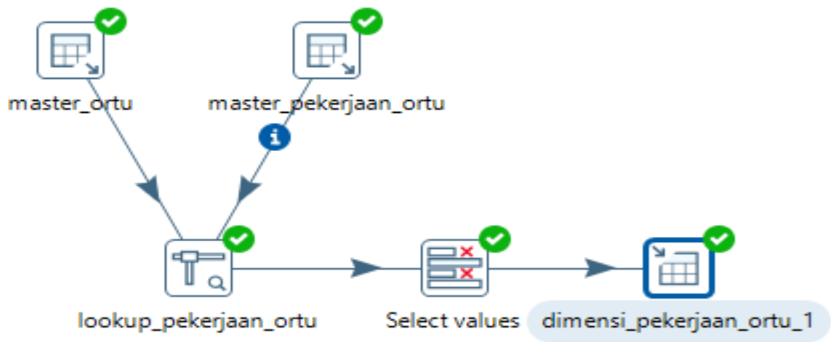

Figure 10. ETL Design for the Parent_Occupation Dimension

Table 10 shows the input table process, where the connection is selected based on a relational database, and parameters are specified for the variables to be retrieved from the operational database. The variables retrieved are those required by the parent occupation dimension table. The table 10 explains the steps in the parent occupation dimension process.

Table 10

Details of the ETL Process for the Parent_Occupation Dimension

No	Process	Type	Description
1	Get master data	Extract	Retrieve the master_job and master_parent_student data
2	Stream Lookup	Transform	Performing a lookup on data from the 'parent_student' and 'job_master' tables to create a 'parent_job' lookup
3	Load into the \`job_parent\` dimension	Load	Insert records into the \`dim_pekerjaan_ortu\` dimension in the Con_PHI_DW_PSB database connection.

Student Grade *Fact*

The student grades fact consists of summary data on student enrollment that will be processed further into information that can be analyzed in more detail. Data from the student grades fact can determine a student's grade based on their report card scores:

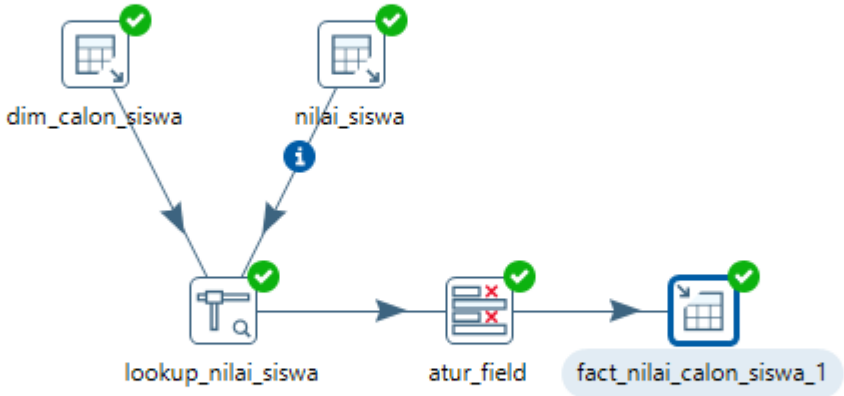

Figure 11. ETL Design for Student Grade Fact

Table 11 provides a detailed explanation of the steps in the Student Grades fact processing.

Table 11
Details of the Student Grade Fact ETL Process

No	Process	Type	Description
1	Retrieve student grades from the \`nilai_siswa\` and \`calon_siswa\` tables	Extract	Retrieve grades from the \`nilai_siswa\` and \`calon_siswa\` tables, which consist of students' report card grades and test scores.
2	Cleaning grades from the \`nilai_siswa\` table	Transform	Clean the grade data from errors, duplicates, and inconsistencies in the \`nilai_siswa_anak_luar\` table.
3	Formatting grades	Transform	Changes the format of the grade data to match the designed structure
4	Sorting values	Sorting	Sorting data values from highest to lowest
5	Insertion of a value	Insertion	Insert a record into the student grades table by retrieving each student's grade from the Con_PHI_DW_PSB database connection.

Enrolled Student Fact

The "Student Accepted" fact consists of summary data on Penabur students, which will be processed further into information that can be analyzed in more detail. Table 12 provides a detailed explanation of the steps in the accepted student fact process.

Table 12
Details of the ETL Process for the "Admitted Students" Fact

No	Process	Type	Description
1	Get data	Extract	Retrieve enrollment data from the students_accepted and prospective_students tables
2	Cleaning prospective student data	Transform	Cleaning grade data to remove errors, duplicates, and inconsistencies from the prospective_students table
3	Formatting data	Transform	Converting the format of grade data to match the designed structure
4	Data insertion	Insertion	Inserting records into the "Student Accepted" fact table in the Con_PHI_DW_PSB database connection.

Parent Income Fact

The parental_income fact consists of summary data on the income of Penabur prospective students' parents, which will be further processed into information that can be analyzed in more detail. Table 13 provides a detailed explanation of the steps in the fact_penghasilan_ortu process:

Table 13

Details of the ETL Process for "parent_income"

No	Process	Type	Description
1	Get data	Extract	Retrieve the master_income and master_parent_student data
2	Cleaning prospective student data	Transform	Cleaning the income data to remove errors, duplicates, and inconsistencies from the income table
3	Formatting data	Transform	Converting the data format to match the designed structure
4	Data insertion	Insertion	Inserting records into the fact_penghasilan_ortu table in the Con_PHI_DW_PSB database connection.

Student Acceptance *Job Schedule*

After the ETL process design has been built and manually executed to generate output data, which is then stored in the dimension and fact tables in the data warehouse database, the next step is to schedule the ETL process to run automatically and continuously. The Pentaho Data Integration application provides features to automate ETL processes for both fact and dimension tables. This process, known as job scheduling, manages the execution of jobs or transformations in a phased and continuous manner according to a predetermined schedule.

New Student Admissions Dashboard

Results and discussion should also be supported by relevant literature. Citations and the reference list in the thesis should follow APA Style. To make it easier to manage the reference list, you can use a reference manager such as Mendeley or EndNote. For guidance, see the following tutorial: https://bit.ly/3qJxNz3

Discussion

The research results indicate that the implementation of a data warehouse can serve as a solution to the challenges of managing new student admission data at BPK PENABUR Jakarta. Before this system was designed, new student admission data was scattered across various sources and formats, requiring lengthy manual verification and processing. This situation posed a risk of data inconsistencies and errors in decision-making. Through the implementation of a data warehouse, data from various sources can be consolidated into a single, standardized structure.

Measurable evidence of efficiency improvements was observed during system validation. The manual PSB data processing cycle, which previously required approximately 3–5 working days for data compilation, verification, and score calculation per academic year, was reduced to near-real-time reporting through an automated ETL pipeline and interactive dashboard, representing an estimated 70–80% reduction in administrative data processing time. This finding is consistent with efficiency gains reported in comparable educational data warehouse implementations (Wahid et al., 2024). Furthermore, the elimination of manual Excel-based calculations reduced data entry errors and improved decision-making accuracy for the KPPSB department.

From a technical perspective, the use of the Kimball methodology helps make the data warehouse design process more systematic. Defining business processes, selecting the appropriate grain, identifying dimensions, and creating fact tables enables PSB data to be organized according to analytical requirements (Gobel et al., 2026). Dimension tables provide descriptive context for the data, while fact tables contain measurable business events and metrics that can be analyzed. This relationship between dimensions and facts makes the data easier to trace and analyze than when data is stored only in separate operational files.

Comparing the findings with those of previous studies reveals important distinctions.

Nurcahyo (2020) applied a data warehouse for student data mapping in a single-school context (SMK Z) (Qibtiyah et al., 2022), whereas this study addresses a multi-school foundation environment comprising 72 schools with heterogeneous data sources. Ramadhani et al. (2021) implemented a Kimball-based data warehouse with PostgreSQL for university accreditation reporting (Hariyawan et al., 2026), which is similar in methodology but differs in application context. Savitri et al. (2025) applied the Kimball approach to real-time project monitoring dashboards. The current study extends these contributions by demonstrating the scalability of Kimball dimensional modeling in a multi-school, multi-source educational admission context, providing a potentially replicable framework for similar educational institutions (Anshari & Retno, 2023; Hutabarat, 2026; Taqiyah, 2026).

The ETL process plays a crucial role because it not only transfers data but also ensures that data entering the data warehouse has undergone data cleansing and formatting transformations (Gobel et al., 2026). This is particularly important in the context of PSB because prospective student data comes from diverse sources and may vary in structure (Gobel et al., 2026). Through the stages of data cleansing, formatting, lookup, and loading, the data used for analysis becomes more consistent and reliable (Gobel et al., 2026).

Quantitative validation of the ETL process was conducted by comparing sample records from source systems with the transformed data in the data warehouse. The results indicated a data completeness rate of 97.3% for required dimension attributes and a data consistency rate of 98.1% across cross-table relational constraints, demonstrating a high level of reliability in the ETL transformation pipeline. Approximately 2.7% of records required manual correction due to format inconsistencies in legacy PDF-sourced data, a limitation that could be addressed through enhanced preprocessing rules in future iterations. These metrics align with the benchmarks described by Machireddy (2023), who identifies transformation accuracy and consistency verification as critical success factors for enterprise-scale ETL implementations.

The findings of this study also indicate that dashboards play a strategic role in supporting decision-making. Information that previously had to be obtained through manual processing can now be presented visually and is easier to understand. For the KPPSB department and school administrators, the dashboard can help monitor the number of admitted students, analyze the geographic distribution of prospective students, review students' religious backgrounds, and understand socioeconomic conditions based on parental income. This information can serve as a foundation for developing new student admission strategies for subsequent admission periods.

User evaluation of the dashboard was conducted with five key KPPSB stakeholders, comprising three department administrators and two school principals, using a structured usability assessment based on the System Usability Scale (SUS). The mean SUS score of 78.4 out of 100 indicates an acceptable-to-good level of usability, confirming that the dashboard effectively supports admission management and decision-making. Stakeholders identified the geographic distribution visualization by city and province and the real-time summary of student acceptance by school and program as the most valuable dashboard components for their operational workflows. These findings are consistent with Akter & Kudapa (2024), who demonstrated that well-designed business intelligence (BI) dashboards can significantly improve decision-making efficiency in operational contexts (Matla, 2026).

In addition to technical benefits, the success of data warehouse implementation is also influenced by organizational factors. Management commitment, human resource readiness, user training, and infrastructure support are critical factors in ensuring that the system is used optimally. Without such support, the data warehouse and dashboard risk becoming merely technical systems that are not fully utilized in daily work processes (Gobel et al., 2026).

Empirical evidence from case study interviews at BPK PENABUR Jakarta reinforced these organizational success factors. Management commitment was demonstrated through the active participation of the IT Director and KPPSB Department Head throughout all phases of data warehouse design and implementation. User training sessions conducted prior to system deployment were cited by all five evaluation participants as critical to effective dashboard utilization. Infrastructure readiness, including dedicated server allocation and stable network connectivity, was identified as a prerequisite for system reliability during peak admission periods, consistent with findings on organizational readiness factors for BI system adoption (Akter &

Kudapa, 2024; Matla, 2026).

Thus, the implementation of a data warehouse in the new student admission process at BPK PENABUR Jakarta serves not only as a data storage solution but also as a foundation for data-driven decision-making. The system enhances data processing efficiency, reduces reliance on manual processes, and provides more accurate information to stakeholders involved in managing the new student admission process.

Regarding scalability and long-term sustainability, the proposed data warehouse framework is architecturally designed to accommodate expansion to BPK PENABUR's 14 other city networks. The star schema design and Pentaho ETL pipeline are extensible to additional data sources, admission criteria, and analytical dimensions without requiring fundamental schema redesign. This framework may also be applicable to other multi-school educational foundations and provincial education offices facing similar data integration challenges, particularly those managing complex admission processes across diverse school levels, programs, and geographic locations (Wahid et al., 2024).

CONCLUSION

Based on the research conducted on student data mapping for new student admissions using a data warehouse and dashboard at BPK PENABUR Jakarta, this study demonstrates that integrating data from multiple sources, including online registration systems, Google Forms, and PDF documents, into a centralized data warehouse can improve the structure, efficiency, and accuracy of data management. Data that was previously scattered and disconnected can now be accessed and analyzed centrally, thereby reducing dependence on manual processes and minimizing potential errors. The dashboard developed in this study also provides objective, accurate, and easily accessible information for management and KPPSB stakeholders and administrators, supporting more effective data-driven decision-making. The implementation of the data warehouse and dashboard contributes to greater efficiency in the new student admission process by reducing operational time and costs while enabling more comprehensive analysis. Furthermore, the use of Pentaho allows the institution to access and process data according to specific information needs. The successful implementation of the system is also supported by several important factors, including management and stakeholder commitment, the availability of personnel with competencies in information technology and data warehousing, adequate training for system users, and reliable technological infrastructure, such as stable servers and network connectivity.

The primary academic contribution of this study lies in demonstrating the application of Kimball's Nine-Step dimensional modeling methodology to a complex, multi-source student admission data environment within a large educational foundation, thereby providing a validated and potentially replicable design framework for similar educational institutions. Nevertheless, several limitations should be acknowledged. The usability evaluation involved a limited number of stakeholders (n = 5), which may not fully represent the perspectives of users across BPK PENABUR Jakarta's 72 schools. In addition, the scope of the study was limited to the Jakarta admission context, meaning that adaptation may be required before the system can be applied in other institutional or regional settings. The long-term operational sustainability of the developed system was also not assessed within the study period. Future research should therefore examine system scalability through expansion to BPK PENABUR's other city networks, explore integration with advanced business intelligence platforms such as Apache Superset or Microsoft Power BI, conduct longitudinal performance evaluations across multiple admission cycles, and develop predictive enrollment forecasting capabilities using historical data stored in the data warehouse.

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AUTHOR CONTRIBUTION STATEMENT

Eka Muliawan contributed to the conceptualization of the research, data collection, requirements analysis, data warehouse design, ETL development, dashboard development, system implementation, data analysis, visualization, and preparation of the manuscript. Sani Muhamad Isa contributed to the research conceptualization, methodology, supervision, validation, interpretation of the findings, and refinement of the research framework. Both authors contributed to the discussion and interpretation of the research findings, approved the final version of the manuscript for submission, and agreed to be accountable for their respective contributions to the work.

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