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Design of a Data Mart for Optimizing Product Sales Analysis at PT. X

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Abstract

With the advancement of technology, companies can now efficiently manage and analyze their data, providing valuable insights that support better business decisions. PT. X is one such company that wants to leverage this capability to optimize its sales data analysis. Therefore, the goal of this study is to design an effective data mart. During the development process, we used Kimbal's Nine-Step Methodology alongside the ETL (extract, transform, load) process to ensure the data was accurately extracted, transformed, and loaded into the data mart. The outcome of this research is a data mart and star schema tailored to PT. X specific needs. Testing results showed that query execution time increased by 40% and data accuracy improved by 80%. Report generation time was also optimized, resulting in a process that was 83% faster. These results demonstrate how a well-structured data mart can improve decision-making efficiency and data reliability.

Keywords: *Sales; Data Mart; Star Schema; Fact Table; ETL*

1. Introduction

The rapid development of information technology across all aspects of life has become a key driver in advancing various sectors, including data management [1], [2]. The significant role of technology, along with the emergence of innovative and competitive business models, has encouraged business owners and companies to implement digital transformation in their management systems [3], [4]. Digital transformation leverages technological resources to enhance product efficiency, customer experience, services, workflows, and decision-making processes [4], [5)]. Through the application of technology, companies gain the ability to adapt and sustain their presence while navigating the dynamics and challenges of the digital era [6)]. Based on the one world article, data is a global potential power. This leads Data Mart as the one focal point in efficiently transforming data into insights. According to a 2025 Tencent Cloud, companies that use a data mart have several advantages, such as improved company performance, simplified data management, enhanced decision-making, and most importantly cost-effectiveness. In addition, those users would quickly access critical insights without wasting much time looking after broader data. Including PT. X, still rely on manual data processing systems, which leads to inefficiency and decision delays. This highlights the importance of developing structured data management solutions, such as data marts, to enhance competitiveness and operational agility [7], [8], [9].

In today's industrial landscape, many organizations in Indonesia—including PT. X—still struggle to transform their data management practices to keep pace with the demands of digital transformation. Studies show that nearly 60% of companies undergoing digital transformation face challenges related to fragmented data systems, limited interdepartmental integration, and low data accessibility [4],[6]. At PT. X, product sales data is still managed manually through a spreadsheet-based system, resulting in repetitive records, limited analytical capabilities, and delays in report generation. Similar issues have been documented in previous studies, where inefficient data storage and lack of visualization hinder timely decision-making and performance monitoring [1],[3]. This inefficiency has measurable impacts—report generation takes an average of 30 minutes and data accuracy error rates reach approximately 5%. Poor data governance and the absence of a centralized data repository significantly reduce operational responsiveness and analytical precision [10]. Therefore, a more structured and automated solution for managing sales data is essential to improve decision-making and overall organizational performance.

Accurate, timely, and cost-efficient data and information management has become one of the most critical resources for a company's success [10]. Managed data is primarily used as a basis for consideration in determining and making company decisions [10)], [11]. To optimize effective data management, Business Intelligence (BI) must be implemented within the company's system. By utilizing BI, companies can integrate, collect, and analyze data comprehensively, providing broader insights to support the decision-making process [12], [13], [14].

An essential element in the implementation of Business Intelligence (BI) is the data mart. A data mart allows the organization to store, integrate, and analyze data efficiently by using a star schema and ETL (Extract, Transform, Load) processes, ensuring data consistency and accessibility. Previous studies have demonstrated that implementing a data mart can improve query response times by up to 50% and enhance decision accuracy by 30% [15], [16]. It serves as a repository for relevant data, acting as a tool for analysis and reporting to address business requirements and improve data accessibility for users [17], [18]. By leveraging data marts, companies can more easily perform market and customer segmentation, manage sales data, and monitor product performance in the market [17]. Data marts also play a crucial role in providing complete and accurate information that simplifies and supports data-driven decision-making. This helps companies adapt more quickly to market changes [19].

The utilization of a data mart enables more accurate and optimal company analysis, allowing the organization to enhance sales strategies, identify market opportunities, and improve overall operational efficiency. To optimize product sales analysis for PT. X, the author leverages technological advancements by using a data mart as a tool to enhance the company's management system. Therefore, the main objective of this research is to design and implement a data mart that optimizes product sales analysis at PT. X. Specifically, it aims to develop a data architecture that integrates various sales-related datasets, enhance data accuracy and reporting speed through the ETL process, and support data-driven decision-making for management. The expected benefit is to provide PT. X with an effective analytical tool that reduces manual workload, improves report generation efficiency, and strengthens its competitive position in the digital marketplace.

2. Literature Review

In digital transformation, data management is a strategic asset, with sales data playing a central role. Beyond recording transactions, it provides insights into consumer behavior, market shifts, and organizational performance. The use of big data and digital analytics has been shown to expand business opportunities and strengthen competitiveness [5]. Business Intelligence (BI) integrates data from multiple sources to support strategic and operational decision-making [10],[11]. A critical component of BI is the data mart, which is a subject-oriented subset of a data warehouse designed to meet specific business needs [16],[17]. For instance, in small and medium enterprises (SMEs), data marts enable faster access to sales and customer data without requiring large-scale infrastructure [19]. Within this ecosystem, the data mart remains one of the most practical BI components, offering subject-oriented data consolidation tailored for specific business needs.

Previous studies have explored data mart development across diverse sectors. Mohammed et al. [12] integration of data marts has significantly improved analytical capabilities in the banking sector. Hamad et al. [13] was also highlighted the relevance of BI tools in educational contexts, showing improvements in performance monitoring when structured data repositories were used. These align with longstanding dimensional modeling principles popularized by Kimball and Inmon [15], [16], [17], [18]. Rainardi [19] similarly underscored the value of well-designed dimensional structures for accelerating data retrieval in operational environments. Fonggo et al. [2] demonstrated how a structured ordering and payment system reduced redundancy and facilitated data capture for downstream analytics. While Allen et al. [3] stressed that visualization driven by structured data repositories improves how organizations interpret operational behavior. Likewise, Yu [1] and Kraus et al. [5] discussed how structured digital ecosystems enhance efficiency, particularly when paired with consistent data models and integrated analytical workflows. Data mart is focused subsets of data warehouses and give business units faster access to relevant information and are especially practical for small and medium enterprises, as they reduce complexity without requiring full-scale systems [4],[3]. Their architecture usually follows a star schema, where the fact table holds key quantitative measures, such as sales values, and connects to supporting dimension tables for multidimensional analysis [4],[5].

The schema relies on the ETL (Extract, Transform, Load) process to standardize data from multiple sources. As integration now includes IoT, e-commerce, and social media, ETL has grown more complex [4]. Its effectiveness can be enhanced through visualization tools, which help reveal hidden patterns and improve decision-making [3]. Recent literature also highlights advancements in ETL processes, which play a central role in ensuring the reliability of data marts. Dhaouadi et al. [21] and Walha et al. [23] compared classical ETL frameworks to emerging big-data-oriented architectures, pointing out the growing need for scalability and automation. Dinesh and Devi [25] expanded this view through hybrid optimization approaches in cloud-based ETL systems, emphasizing reliability, performance, and adaptability. Biplob and Haque [22] proposed more efficient extraction and transformation methods, further supporting the development of high-performance data marts. These studies collectively indicate that the quality of ETL processes directly influences the dependability and analytical power of data marts.

Recent research emphasizes the shift of ETL toward automation, scalability, and cloud integration to accommodate massive, real-time data processing [22], [25]. Studies such as Walha et al. [23] and Dhaouadi et al. [21] compare traditional ETL frameworks with modern big data-oriented architectures, highlighting the growing importance of parallel processing and hybrid optimization in achieving high performance and reliability. The other studies demonstrate the impact of data mart implementations on business performance. For example, Fonggo et al. [2] designed a web-based ordering and payment system that streamlined data collection for business analysis. Similarly, Bany Mohammed et al. [12] found that BI systems integrating data marts improved decision-making efficiency in the banking sector, while Hamad et al. [13] reported that data-driven educational systems significantly enhanced performance tracking and forecasting accuracy. These studies illustrate how domain-specific data marts such as those for sales, inventory, or customer service enable organizations to transform raw data into actionable insights.

Prior studies have examined dimensional modeling, ETL enhancements, and BI applications across various industries, few have specifically addressed the optimization of product sales analysis within small-to-medium organizations that still rely on manual or spreadsheet. The present research advances the state of the art by integrating Kimball’s Nine-Step Methodology, a structured ETL transformation pipeline, and an empirically validated performance assessment within the context of PT. X. This study delivers a practical, domain-specific data mart design that demonstrates measurable improvements in query speed, data accuracy, and reporting efficiency.

3. Methods

Data collection for this study was conducted through direct interviews with a single stakeholder at PT. X. The data obtained consists of product sales records at PT. X spanning two years, from 2023 to 2024. The data was personally provided to the researcher in document format. The data mart is designed using Kimball's Nine-Step Design Methodology and the ETL (Extract, Transform, Load) process.

3.1. Nine-step Design Methodology

The method used in the creation of the data mart for optimizing product sales analysis at PT. X is the Nine-Step Design Methodology (15). Below are the steps in this methodology:

1) Choose the process.
2) Choose the grain
3) Identify and Conform the Dimensions
4) Choose the facts
5) Store precalculation in the fact table
6) Round out the dimension table
7) Choose the durations of the data mart
8) Determine the need to track slowly changing dimensions
9) Decide the physical design

3.2. ETL (Extract, Transform, Load)

ETL (Extract, Transform, Load) is a data movement method that has been applied in various forms since the introduction of the first enterprise data warehouse (20). This method is used to extract data from various source systems, transform it to meet the company's analysis needs (15).
ETL is also essential for the process of transferring and transforming company data. It plays a crucial role in ensuring that data is moved efficiently and processed accurately to support strategic business decisions (21), (22).

The ETL process provides significant advantages in managing large volumes of data from various systems. Additionally, ETL ensures data quality and consistency, making further analysis more straightforward. With structured and integrated data, decision-making can be performed more efficiently (23), (24). By utilizing ETL, companies can enhance operational efficiency and maximize the use of data to support business intelligence activities such as data mining and machine learning (25).

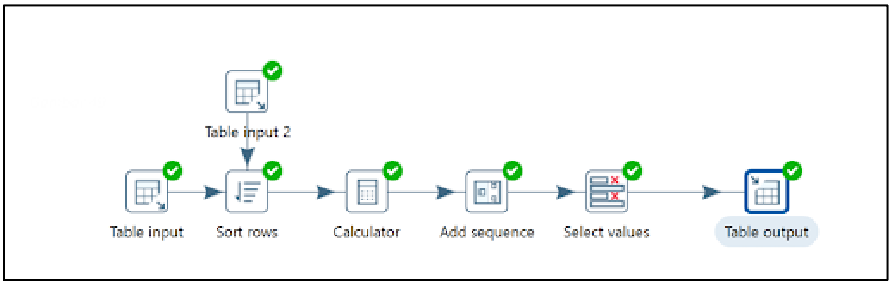

Figure 1. Time Dimension Transformation

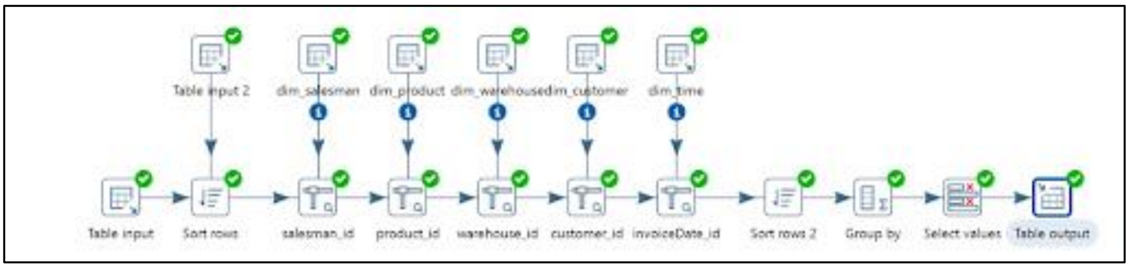

Figure 2. Fact Sales Transformation

4. Results and Discussion

4.1 Result

The aim of this research is to design a data mart based on the product sales data of PT. X. The design of this data mart is intended to help stakeholders better understand and enhance the efficiency of the data analysis process. The researcher develops an architecture that outlines the workflow of the data mart design process, serving as a tool to explain and detail the steps involved in the creation and implementation of the data mart.

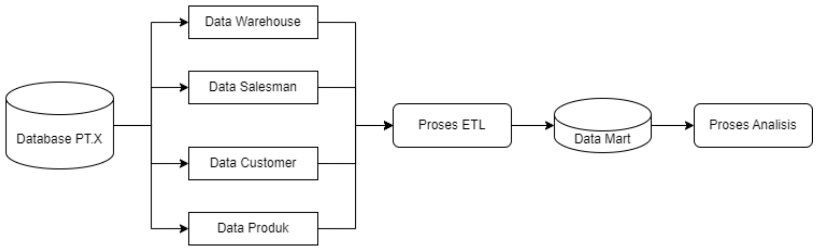

Figure 2. Data Mart Design Architecture for PT. X

Each phase of Kimball's Nine-Step Methodology was carefully executed to ensure the proposed data mart effectively supports sales analysis at PT. X. In the main business process selected was product sales transactions, as they directly reflect company performance and strategic opportunities. Phase 2, defined the transaction-level data as the analysis focus, allowing for detailed tracking of individual product sales. Phase 3, established consistent dimension tables warehouse, salesman, customer, product, and time standardizing attributes to maintain integrity across data sources. In Phase 4, quantitative measures such as total sales, quantity, and transaction amount were determined as key analytical indicators. Phase, integrated computed values such as monthly and yearly sales totals to enhance query efficiency. Phase 6, refined each dimension with descriptive attributes to support richer analytical contexts. Phase 7, selected data from January 2022 to December 2023 to capture two years of complete sales trends. Phase 8, defined mechanisms for handling attribute updates over time without compromising historical consistency. Phase 9, implemented the star schema using SQL Server and Pentaho.

The star schema in **Figure.2** is used to organizing a central fact table that contains quantitative data or key metrics. This fact table is surrounded by several dimension tables that store descriptive attributes such as time, product, and location. This structure resembles the shape of a star, where the fact table acts as the core, and the dimension tables serve as the "branches" that connect related attributes. The main advantage of this star schema is its ability to speed up the processing of analytical queries, facilitate understanding of relationships between data, and improve the efficiency of processing large volumes of data. The following is a Star Schema that describes product sales data from PT. X:

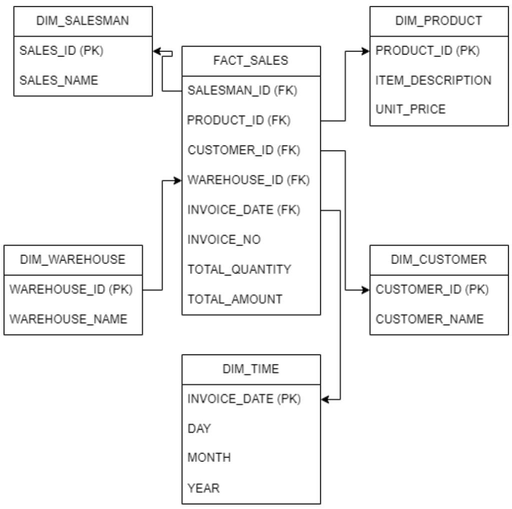

Figure 3. Star Schema of PT.X Product Sales Data

The stages carried out by researchers in the data mart design process follow the Nine-step Design methodology by Kimball. The following is a description of the nine steps or stages of the design methodology by Kimball during the data mart design process:

Choose the process**,** in this phase, the researcher selects product sales transactions at PT. X as the business process and focus for the data mart design. This choice is made because sales transaction data is a crucial aspect that can be analyzed to support better decision-making. Designing a data mart focused on product sales transactions can help the company understand market opportunities, identify sales patterns, and improve sales with more effective strategies. The data used for this design includes data warehouse, salesman data, invoice data, date data, and product data.

Choose the grain**,** this phase is the key step in designing the fact tables, where selected data is determined for use in the data mart design for PT. X. These data are obtained personally and provided directly in document format by one of the stakeholders at PT. X. dentify and Conform the Dimensions, the following are the dimension tables and meta data that have been designed by the researcher:

Table 1. Warehouse Dimension Table from PT. X Product Sales Data

Warehouse Dimension					
Column Name	Data Type	Transform	Source	Size	Description
Warehouse ID (Primary Key)	Integer	Create	-	4	Unique ID per warehouse
Warehouse Name	String	Copy	Warehouse	4	Name of the warehouse where the transaction took place

Table 2. Salesman Dimension Table from PT. X Product Sales Data

Salesman Dimension					
Column Name	Data Type	Transform	Source	Size	Description
Salesman ID (Primary Key)	Integer	Create	-	5	Unique ID per salesman
Salesman Name	String	Copy	Salesman	40	Name of the salesman who sold the product

Table 3. Customer Dimension Table from PT. X Product Sales Data

Customer Dimension					
Column Name	Data Type	Transform	Source	Size	Description
Customer ID (Primary Key)	Integer	Create	-	6	Unique ID per customer
Customer Name	String	Copy	Customer	40	Name of the customer who sold the product

Table 4. Product Dimension Table from PT. X Product Sales Data

Product Dimension					
Column Name	Data Type	Transform	Source	Size	Description
Product ID (Primary Key)	Integer	Create	-	10	Unique ID per product
Description	String	Copy	Product	100	Product Description
Unit Price	Float	Copy	Product	30	Price per Product Unit

Table 5. Time Dimension Table of PT. X Product Sales Data

Time Dimension					
Column Name	Data Type	Transform	Source	Size	Description
Invoice Date (Primary Key)	Integer	Copy	Invoice	10	Sales transaction date
Day	Integer	Create	-	2	Sales transaction day
Month	Integer	Create	-	2	Sales transaction month
Year	Integer	Create	-	4	Sales transaction year

Store precalculations in the fact table, at this stage, important pre-calculations are stored in the fact table to facilitate analysis and improve the efficiency of the data processing. Some pre-calculations that have been included in the data mart include total sales per month, total sales per product, and total sales per year.

Choose the facts, this stage aims to determine and build the fact table that will be used in the data mart design process. This table will contain quantitative data related to product sales transactions of PT. X. The determination of this fact table is crucial as it serves as the foundation for data analysis and provides a comprehensive overview of business performance, which can be further processed for strategic decision-making. Below is the fact table that has been created by the researcher:

Table 6. Fact Table from PT. X Product Sales Data

Fact Table					
Column Name	Data Type	Transform	Source	Size	Description
Salesman ID (Primary Key)	Integer	Create	-	5	Unique ID per salesman
Product ID (Primary Key)	Integer	Create	-	10	Unique ID per product
Customer ID (Primary Key)	Integer	Create	-	6	Unique ID per customer
Warehouse ID (Primary Key)	Integer	Create	-	4	Unique ID per warehouse
Invoice Date (Primary Key)	Integer	Copy	Invoice	10	Sales transaction date
Invoice No	Integer	Copy	Invoice	9	Unique ID per transaction
Total Quantity	Integer	Create	-	10	Total product sold
Total Amount	Integer	Create	-	20	Total earning

Round out the dimension table, at this stage, the researcher adds appropriate descriptions to complement the dimension tables that have been created. These descriptions are added to explain each entity and attribute in the dimension tables. The purpose of this description is to interpret the presented information more accurately and effectively. By completing the dimension tables, the data mart can provide a data structure that is informative to support deeper analysis and more precise decision-making for the company.

Choose the durations of the data mart, the researcher has determined the duration of the data to be used in the data mart design, which includes product sales transaction data from PT. X for the period of January 2022 to December 2023. This time frame was selected to ensure that the data mart encompasses sales information over two full years, providing a comprehensive overview of sales trends, demand changes, and product performance during this period.

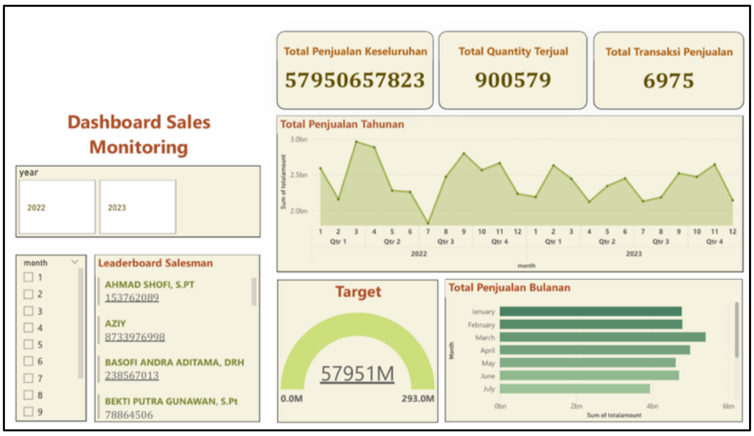

Figure 4. Dashboard Interface

Determine the need to track slowly changing dimensions, Over-time, some attributes in the dimension will undergo gradual changes. Therefore, the researcher will evaluate and determine the appropriate method to manage these changes to ensure they can still be integrated into the data mart without disrupting the consistency of the previous data. The researcher will make improvements such as updating new data in the created dimensions, adding new attributes, and rewriting attributes that have undergone changes.

Decide the physical design, this stage encompasses all ETL processes during the data mart design. The researcher extracts data from the provided documents and reconstructs it using SQL Server Management Studio 20. Then, the researcher performs the data transformation phase using the Pentaho application. This transformation is carried out to clean the data by removing missing, duplicated, unordered, and incomplete entries. Afterward, the researcher will input the normalized data into the data mart and load it into the SQL Server Management Studio 20 application.

After implementing the data mart at PT. X, there were noticeable improvements in query execution speed, data accuracy, and report generate efficiency. Before the data mart, running queries on raw sales required an average of 7 seconds due to the complexity of joins, while after implementing the star schema, query execution time improved by 40%, reducing it to 4.2 seconds. Data accuracy also improved, as the initial 5% error rate caused by missing or inconsistent values was reduced to 1%, marking an 80% increase in data reliability through the ETL process. Additionally, report generate time was optimized, decreasing from 30 minutes to just 5 minutes, an 83% improvement, enabling faster decision-making.

All these numbers and improvements come directly from interviews conducted with users before and after implementing the system. The interviews were held separately to ensure that responses were based solely on their experiences and perceptions without any bias. Their responses confirmed that the data mart significantly improved how they manage and analyze sales data, making their work smoother and more efficient. This shows how a well-structured data mart, combined with a star schema and ETL process, can truly reinforce the role of modern data management solutions in supporting business intelligence and competitive advantages.

4.2 Discussion

The research demonstrates a clear alignment and addresses the inefficiencies inherent in manual and spreadsheet-based systems. Before the implementation, report generation required an average of 30 minutes, with an error rate of approximately 5%. Post-implementation, query execution speed improved by 40%, error rates reduced to 1%, and report generation time decreased to just 5 minutes. These results suggest that the proposed model effectively achieves the intended objectives, confirming its practical utility in the business context.

Comparatively, several previous studies provide benchmarks that underscore the validity of these outcomes. Fonggo et al. [2] implemented a web-based ordering system to streamline data capture, which improved data accessibility and reporting accuracy. Similarly, Mohammed et al. [12] demonstrated that integrating data marts in banking systems enhanced decision-making efficiency and analytical reliability. Findings of this research align with these benchmarks, confirming that a well-designed data mart with a star schema and robust ETL process can systematically enhance data accuracy, query efficiency, and operational responsiveness in the context of sales data analysis.

Additionally, the research addresses gaps noted in prior studies. While Verhoef et al. [6] and Kraus et al. [5] highlighted challenges in fragmented data systems during digital transformation, this study shows that a structured data mart mitigates these issues by integrating sales, customer, product, and time dimensions into a coherent analytical framework. Furthermore, the findings suggest synergies with previous literature: for instance, the automation and standardization benefits highlighted by Walha et al. [23] and Dinesh and Devi [25] are realized concretely in this implementation. On the other hand, the study also provides a point of contrast to certain approaches, such as large-scale cloud-based ETL architectures [22], by showing that significant improvements can be achieved even within localized, on-premise environments with moderate data volumes, making the solution more accessible to SMEs.

In terms of scientific contribution, this study integrates its findings into the broader set of existing research by demonstrating the practical effectiveness of data mart design in a real-world sales context. It confirms, extends, and operationalizes theoretical principles of dimensional modeling, ETL optimization, and business intelligence application. This positions the research as a bridge between conceptual understanding and applied implementation, offering both a reference model for SMEs and a validated benchmark for future studies aiming to optimize sales data analysis. In sum, the study provides empirical evidence that supports prior research while also highlighting the flexibility and adaptability of structured data marts in improving operational decision-making.

5. Conclusion

This study discusses the design of a data mart for the product sales data of PT. X. Based on the results of the data mart design that has been created, it can be concluded that the data is now in a structured form and can be used as a tool for analyzing product sales at PT. X. This design was created according to Kimball's Nine-Step Design Methodology and also involves the ETL process. With the establishment of a data mart that presents information and data in an easily understandable format, the decision-making process will be more efficient than before. Therefore, this research can support and assist PT. X in optimizing its product sales data analysis.

Based on the results and validation outcomes, the implementation of the proposed data mart demonstrated measurable improvements in data processing performance and analytical accuracy. Specifically, query execution speed increased by 40% (from 7 seconds to 4.2 seconds), data accuracy improved by 80% (error rate reduced from 5% to 1%), and report generation time decreased by 83% (from 30 minutes to 5 minutes). These findings confirm that the designed data mart significantly enhances the efficiency of data retrieval, processing, and reporting compared to the previous manual or unstructured approach. The validation results obtained through user interviews further confirmed that the data mart facilitates faster, more reliable, and more comprehensible access to sales information. Users reported smoother workflows, reduced redundancy, and greater confidence in the accuracy of analytical outputs. These outcomes collectively indicate that the developed model effectively supports the company's goal of achieving a more data-driven and responsive decision-making process.

In conclusion, the research successfully validates that the implementation of a data mart based on Kimball's methodology and ETL integration can optimize product sales data analysis at PT. X. The system not only improves performance metrics but also provides a sustainable framework for future data analytics initiatives. Therefore, this model can serve as a reference for other organizations aiming to enhance their sales performance analysis through structured and intelligent data management systems.

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