Asian Journal of Computer Science and Technology
ISSN: 2249-0701 (P); 2583-7907 (E)
Vol.14 No.1, 2025, pp. 57-65
© Centre for Research and Innovation
www.crijournals.org
DOI: https://doi.org/10.70112/ajcst-2025.14.1.4325

Design and Implementation of Data Warehousing for Small and Medium Sized Enterprises (SMEs): A Cost-Effective Approach in Online Stores

Mohamed Buhary Fathima Sanjeetha[1*] and Dinesh Asanka[2]
[1]Department of Management and IT, South Eastern University of Sri Lanka, Oluvil, Sri Lanka
[2]Department of Industrial Management, University of Kelaniya, Sri Lanka
E-mail: dasanka@kln.ac.lk
*Corresponding Author: sanjeetha.mit@seu.ac.lk
(Received 4 January 2025; Revised 20 March 2025, Accepted 5 April 2025; Available online 20 April 2025)

***Abstract* - The storage of historical data for reference purposes has been a fundamental practice since the advent of relational databases. Despite their importance, small and medium-sized enterprises (SMEs), particularly online merchants, often rely on rudimentary methods for data storage and retrieval, thereby limiting their ability to utilize data analytics for informed decision-making. This study aims to establish a cost-effective and low-complexity data analytics infrastructure for SMEs to facilitate their transition into data-driven organizations. It examines the effective use of data warehouses (DWs) through office automation tools and open-source software solutions. A comparative analysis of data warehouse schemas-specifically the Star Schema and Snowflake Schema-was conducted to evaluate their effectiveness in preserving data integrity and supporting analytics. A practical implementation using freeware and office automation tools was executed to validate the proposed methodology. The findings indicate that the Star Schema is more suitable for dynamic data environments requiring frequent updates, whereas the Snowflake Schema is optimal for static data contexts. The proposed infrastructure effectively supports decision-making processes, particularly for online enterprises, by maintaining data integrity and streamlining analytics. This study provides SMEs with a pragmatic and economic framework for implementing data warehousing and analytics technologies. Adoption of the proposed infrastructure enables online enterprises to enhance decision-making and transition towards a data-driven strategy, thereby sustaining competitiveness in the digital marketplace.**
***Keywords*: Data Warehousing, Small and Medium-Sized Enterprises (SMEs), Data Analytics, Star Schema, Open-Source Tools**

I. INTRODUCTION

The purpose of such an implementation is to provide users at small and medium-sized enterprises (SMEs) with a centralized repository of reliable information, enabling the generation of more accurate reports and the precise definition of business needs [1]. Since the inception of computer networks capable of storing databases, information reporting and exchange have been closely associated with the concept of databases. Users now expect information to be shared in ways that are instantaneous, efficient, and secure [2]. However, due to the presence of numerous databases within an organization, efficient data retrieval requires coordinated efforts across all existing systems. This can be achieved through the implementation of an enterprise data warehouse (EDW). The necessity for such a centralized system is more relevant today than ever before.

This paper describes data warehousing methodologies, design considerations, expectations, and challenges-particularly in relation to data cleaning and the transformation of existing data-alongside the common difficulties of extracting data from transactional systems [3]. It also includes a technical component discussing the database requirements and the technologies used to upgrade the data warehouse (DW) [4]. The feasibility of integrating data from multiple registries and warehouses is explored [5]. Furthermore, the paper discusses specific data marts within the warehouse that serve targeted analytical purposes.

Finally, the enterprise data warehouse is designed to be accessed by users through various means, including reporting tools and business intelligence applications. The development of an EDW prototype demonstrates how two distinct databases undergo the Extract, Transform, and Load (ETL) process and are subsequently modelled using star schemas to simplify the reporting process [6]. In a separate but equally important aspect of the study, identical queries were executed on two types of databases-transactional and warehouse-based-to evaluate their performance on a real-world data scenario.

II. PROBLEM STATEMENT

In this scenario, the setup of an SME data warehouse in the context of an online retail environment is an attempt to address the challenge of integrating multiple disparate systems into a unified data source. Information related to employees, shareholders, customers, suppliers, and distributors is often stored across various transactional databases, due to the broad spectrum of internal and external business functions. This fragmented structure creates informational silos, where data does not translate across systems to support the growth and operation of the online store. Reports, which are ultimately consumed by end users, are often delayed due to reliance on third-party schedules, despite those recipients having the most immediate need for insights. This delay is a common issue in the absence of an enterprise data warehouse (EDW). Additionally, users often need to manipulate report data using tools like Microsoft

This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

Excel or Power BI to meet their specific needs-an error-prone process that can lead to misinterpretations. In today's business environment-particularly in the wake of corporate fraud incidents-accurate reporting is more critical than ever, raising questions about the adequacy of current processes.

III. EXPLANATION

The use of data warehouses to enhance decision-making is a fundamental component of business intelligence (BI). In addition to storing information, a data warehouse employs a combination of hardware and software to provide data in user-friendly formats. It supports multiple forms of analysis, including reporting and online analytical processing (OLAP). The wide availability of reporting tools further empowers users to independently retrieve and interact with data, eliminating the need to rely on third parties. The implementation and continued development of a data warehouse transforms it into a powerful tool that enables efficient BI operations.

IV. MOTIVATION

When considering the implementation of a data warehouse for SMEs, several key factors must be taken into account. Although such a project may demand considerable time, resources, and financial investment, the benefits are substantial. Chief among them is the creation of a unified platform for reporting. By consolidating information from all existing databases into a single source, data can be delivered consistently and reliably to users.

One major advantage of reporting from a data warehouse-as opposed to transactional systems-is performance optimization. Transactional databases are not designed for analytical workloads; generating reports from them can burden system resources, potentially degrading performance or causing system unresponsiveness. Moreover, simultaneous insert, update, or delete operations during report generation can compromise data accuracy. In contrast, a data warehouse supports long-term storage of historical data, preserving its integrity over time. Furthermore, once users receive data from the warehouse, they can interact with it to enhance business decision-making. Tools like Excel and Power BI enable users to explore and analyze data through OLAP cubes, key performance indicators (KPIs), and advanced visualizations. With access to this data, users at all levels can create complex models, generate reports, perform computations, and conduct analysis-thereby making more informed decisions for their organizations.

V. RELATED WORK

These days, small and medium-sized enterprises (SMEs) represent the backbone of the global economy. Moreover, they generate massive volumes of data daily based on their operations and processes. To utilize this data effectively, decision-making must be grounded in accurate information-bringing into focus the concept of Business Intelligence (BI). Martin *et al.* [7] are credited with being the first to use the term "business intelligence." In the modern context, however, BI refers to the integration of data for planning and operational optimization. According to Singh *et al.* [8], an organization's resources-including data, applications, people, and processes-must be coordinated to expand organizational knowledge, implement strategy, and adapt to dynamic environments, especially in the context of data warehouse adoption among SMEs such as online stores. The term "business intelligence" has evolved significantly, with a growing number of companies employing BI models to enhance performance and strengthen market position [9].

Researchers define "data warehousing" as a multifaceted concept encompassing architecture, analytical tools, applications, databases, and techniques. Ayoubi and Aljawarneh [10] provided a comprehensive definition, stating that BI systems integrate data from operational systems with analytical tools to supply planners and decision-makers with insightful, competitive information. To achieve this goal, the timeliness and quality of inputs into the decision-making process must be improved. The fundamental objective of BI is to enhance organizational understanding of internal capabilities [11].

Tawfik *et al.* [12] describe BI in terms of three key functions: data capture, data storage, and data access and analysis. These functions involve both internal sources (e.g., operational systems) and external sources (e.g., customers, suppliers, government agencies, competitors, and the internet) [13]. Enterprise systems coordinate data collection, storage, and knowledge management using analytical tools to process complex information efficiently and maintain business continuity. The essential components of these systems include information sources such as operational databases, ETL (Extract, Transform, Load) processes, data mining, analytical applications, data repositories, data warehouses (DW), and online analytical processing (OLAP) technologies [14].

In addition to tracking sales levels and identifying best-selling products at both aggregate and granular levels, IT systems help organizations analyze numerous performance parameters quickly by applying formulas or indicators relevant to each business metric. This is made possible through the extensive range of services that BI systems offer. According to Cherapanukorn [15], the benefits of BI include:

1. The ability to browse data from multiple databases or cloud sources, enabling data correlation and more informed decision-making.
2. Access to relevant data from any location, provided internet connectivity is available.

VI. NEED OF DATA WAREHOUSE

When evaluating the requirements for an SME data warehouse, it is essential to consider all business divisions and their potential contributions. The enterprise system forms the foundation of database reporting in any online business, containing both current and historical information about customers and their locations. Such a system aids in managing repetitive tasks effectively. Given the numerous benefits an SME data warehouse offers, it is important to recognize that building the system requires a dedicated and skilled team.

In today's challenging financial environment-where budgets are tight and expenditures are heavily scrutinized by senior leadership-strong advocacy from the executive sponsor and business stakeholders is critical to promote and justify such a major initiative. Since implementation is a pivotal phase, the IT department is typically responsible for setting up the data warehouse. Notably, successful implementation also hinges on having a committed executive sponsor [16]. The data warehouse should be developed in alignment with the reporting needs of specific business units.

A. Data Sources

The data sources for the online store span various functional domains and business processes. Computerized systems serve as primary data sources, including several perspectives from management and IT systems. Additional sources include structured file formats such as CSV files and Excel spreadsheets, as well as manual records like client invoices, invoice line items, and payment slips.

B. Data Warehouse Requirements

The users of the online store include individuals from diverse roles-senior management, middle managers, front-line employees, suppliers, branch managers, distributors, and marketing executives. Each user group has unique requirements, which are typically classified into functional and non-functional categories.

1. Functional Requirements

These requirements define what the online retailer expects from the data warehouse:

a. *Data Visualization:* Users require various forms of visual representation-charts, graphs, and comparison tables-to interpret query results effectively.
b. *Queries:* OLAP systems should support the creation of multidimensional pivot tables for complex data analysis.
c. *ETL Processes:* Extraction, transformation, and loading (ETL) involve retrieving data from multiple sources, converting it appropriately, and storing it in the data warehouse.
d. *Remote Access:* Users must be able to access the system from various locations via the internet.
e. *Security:* Authorization and access control should be based on the user's role, designation, and level of authority to ensure system security.

2. Non-Functional Requirements

These requirements are considered lower in priority but are still critical for long-term success:

a. *Simplicity:* The system design should be user-friendly, and developers should not require deep specialization to manage or modify it.
b. *Scalability:* The system must be capable of scaling to accommodate future growth in data storage and analytical needs.
c. *Maintainability:* The architecture should support easy modifications and continuous improvements to meet evolving business demands.

VII. BUSINESS ANALYST-DRIVEN DATA WAREHOUSE DESIGN

From the perspective of business analysts (BAs), it is crucial to have a thorough understanding of the insights generated by a data warehouse. Access to a well-designed data warehouse provides a competitive advantage and enables more informed decision-making compared to organizations that do not leverage such systems. Furthermore, the ability of a data warehouse to deliver information on trends, patterns, anomalies, and other critical metrics can contribute to a reduction in overall operational costs. According to this viewpoint, four distinct design perspectives must be considered when developing a data warehouse [14].

A. Data Warehouse Usage: Information Processing

At its core, a data warehouse is used to generate reports and answer queries that are often complex and diverse in nature, tailored to meet various analytical and business needs. These functions can also be aligned with broader strategic goals of the organization. Consequently, selecting the appropriate tools for data warehouse implementation becomes essential. The term "data mining tools" encompasses a broad range of software applications that support these objectives.

The three primary applications of a data warehouse are:

1. *Information Processing:* Supports basic querying, statistical analysis, cross-tabulations, tabular data, and visual representations such as graphs and charts. Data warehouses increasingly utilize cost-effective, web-based tools that allow users to access data through standard web browsers. Both summarized and detailed data are supported.
2. *Online Analytical Processing (OLAP):* Facilitates multidimensional analysis of data warehouse contents, making it particularly useful for in-depth analytical tasks.
3. *Data Mining:* Enables the discovery of hidden patterns and relationships within data, aiding in the development of analytical models for classification and prediction. This application helps uncover previously unknown insights that support strategic decision-making.

These three applications collectively enhance the functionality and usability of data warehouses, making them essential tools for data-driven organizations.

VIII. METHODOLOGY

A. Data Set

For the purpose of this research, an open-source dataset was obtained from Kaggle [17]. The dataset contains transactional data from a typical online retailer and is illustrated in Fig. 1 for this project, as developed by the ML Administration. It includes approximately 90,000 records comprising information on customers, order items, orders, payments, products, and sellers. The dataset is available in .CSV format and consists of six separate files representing various aspects of the online shop.

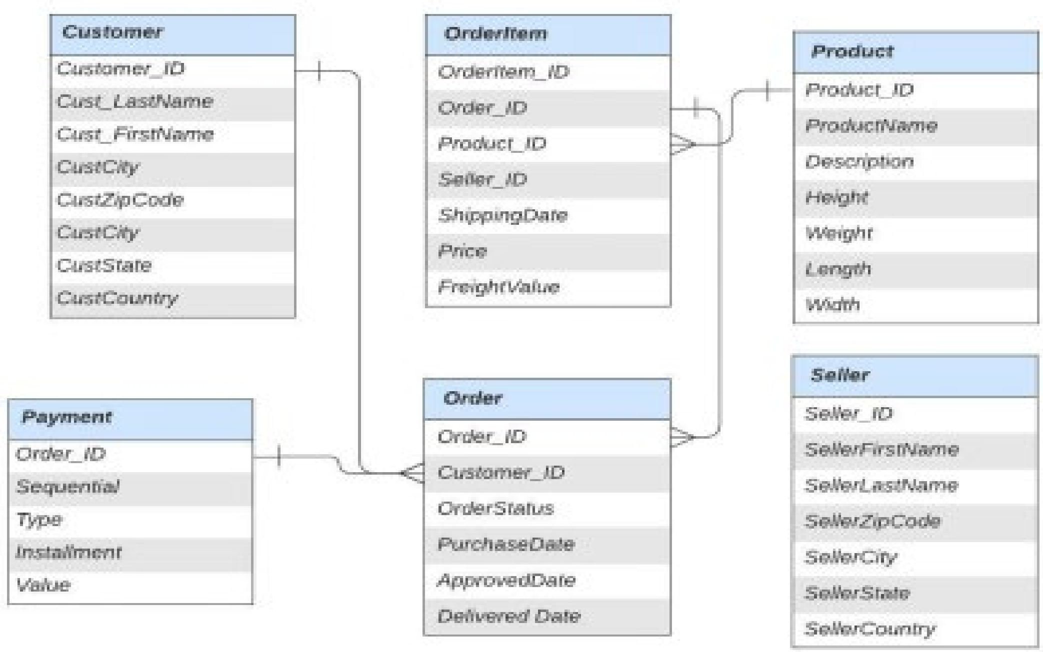

Fig.1 Entity-Relationship Diagram of the OLTP Database

The previously shown relationship diagram includes six tables labeled as follows: Customer, Order Item, Order, Payment, Shipping, and Seller.

B. Data Collection

As an initial step in this process, the researchers collected and prepared the data using Microsoft SQL Server [18]. A database was created to store the imported data. Transactional data from online stores can typically be accessed in two ways: (1) by obtaining raw data in the form of comma-separated value (CSV) files, which can be imported into a database, spreadsheet, or text editing application; and (2) by using an API. For this study, six CSV files were used as the primary data source. A staging environment was created using this data, and a script was developed to upload the data into a data warehouse hosted on Microsoft SQL Server.

C. Business Intelligence

This application enables users to access the SME Data Warehouse, which centralizes data from the company's operational databases. Business intelligence (BI) applications serve as additional components that support a range of functions within the data ecosystem. The Extract, Transform, and Load (ETL) process, a core element of BI, facilitates the transfer of data from transactional source databases into the data warehouse, addressing issues related to data integration and consistency.

D. Reporting

Users outside the IT department can generate reports rapidly; however, doing so without validating data quality can result in mistrust of the data and may lead to incorrect conclusions or downstream issues. Therefore, BI systems must not only deliver data quickly but also support enterprise-wide reporting and analytics.

Microsoft Power BI [19] is a widely adopted tool for data warehouse-driven reporting and dashboards. It enables users to visualize and interact with high-level summaries and detailed data from multiple sources. Dashboards typically include statistics, graphs, sparklines, key performance indicators (KPIs), and summary information. An interactive dashboard may also provide forecasts to assist users in making informed decisions or allow them to drill down into specific problem areas.

IX. DATA WAREHOUSE DESIGN

A. Dimensional Model

This stage, also known as Dimensional Modeling, is responsible for configuring and organizing the final destination of the data. It plays a central role in handling most of the transactional processes. The use of denormalization is not only the most common approach but also the most logical in this context. Although it is technically feasible to use a "transform and load" date, such an approach is not meaningful within the existing architecture. When designing a data warehouse, it is reasonable to assume that end users will require easy access to data for business intelligence purposes.

B. Star Schema

The star schema is a fundamental model used in data warehouse development. In this schema, the fact table is positioned at the center, surrounded by dimension tables, forming a structure that resembles a star-hence the name. Data warehousing typically begins to take shape once the relationships among the dimension tables are defined. The fact table contains foreign keys referencing each of the dimension tables, enabling the star schema structure. This arrangement simplifies data retrieval and enhances the efficiency of reporting.

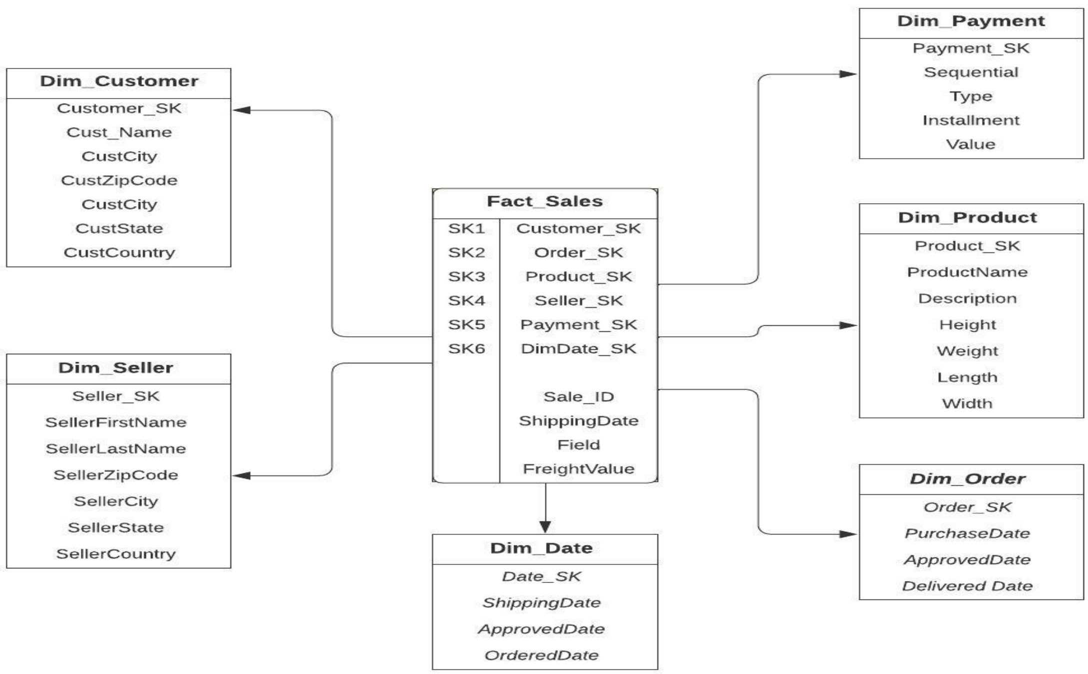

Fig. 2 Online store star schema

Dimension tables closely resemble source data tables and are essential to the star schema architecture. The fact table derives most of its data and attributes from these dimension tables. Dimension tables typically represent key business entities such as products, customers, employees, and facilities, forming highly correlated clusters of organizational data. For example, customer-related information such as addresses and first, middle, and last names is often stored in separate dimension tables. Fig. 3 illustrates the components of a Customer Dimension Table. During the ETL (Extract, Transform, Load) process, data is first loaded into the dimension tables.

Since these tables contain primary keys, they are referenced in the fact table. The primary key in the fact table is the dimension ID, a numeric identifier assigned to an indexed integer field that auto-increments. In SQL Server, this is referred to as an Identity column.

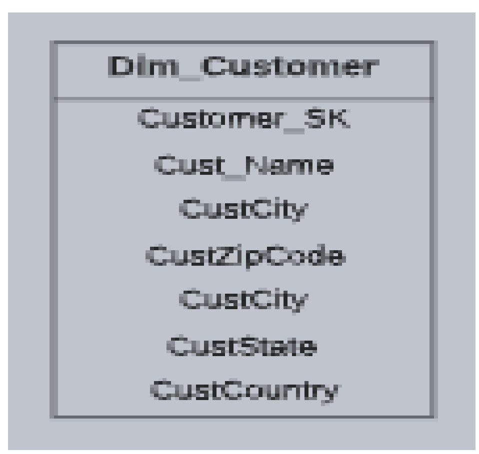

Fig. 3 Customer dimension table

These IDs are generated before the creation of the fact table. For a table to be classified as a fact table, it must contain at least two and no more than six foreign keys (FKs), in addition to a primary key (PK) derived from the dimension tables [20]. This structure allows users to associate fact table transactions or events with attributes from the dimension tables for reporting purposes. In the prototype presented later in this study, Fig. 4 illustrates this relationship. Connecting to the dimension tables only when needed is more efficient than storing all attribute data directly within the fact table. This approach prevents the fact table from becoming overloaded with unnecessary attributes, ensuring better performance and maintainability.

Fig. 4 Fact Sales Table

C. Data Warehouse Architecture

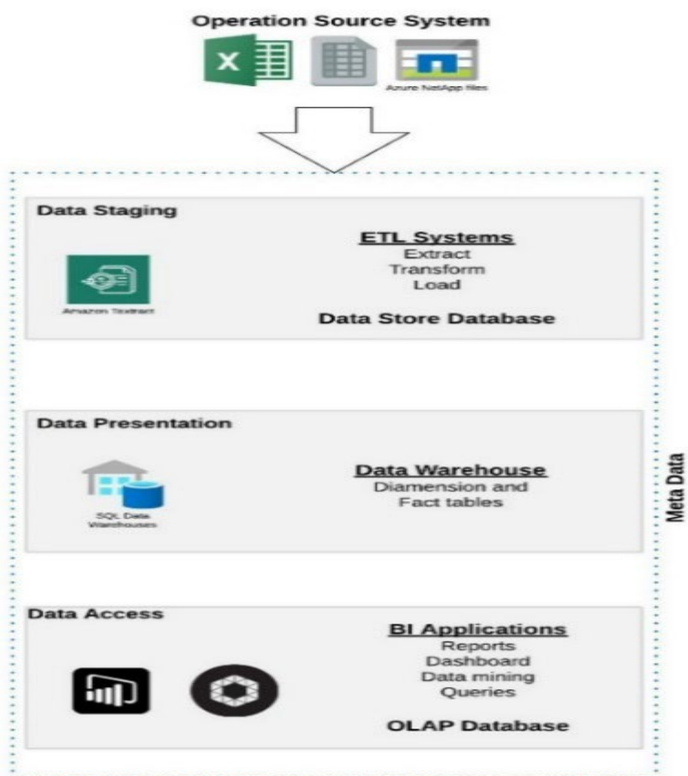

Fig. 5 The Architecture of a Data Warehouse.

X. PROPOSED DESIGN

A. Star Database Structure for the Selected Database

The fact table contains all numerical and quantitative measurements. Dimension tables are related subsets that provide descriptive context to the data stored in the fact table. These tables typically include textual attributes representing key business performance metrics.

To preserve historical records accurately, it is sometimes necessary to use a key that is different from the natural key.

In such cases, surrogate keys (SKs) are used as the primary keys in dimension tables. These SKs uniquely identify each row in the dimension table, even when natural keys change over time.

Fig. 6 illustrates the transformed OLAP data warehouse architecture, showing how dimension and fact tables interact within the system.

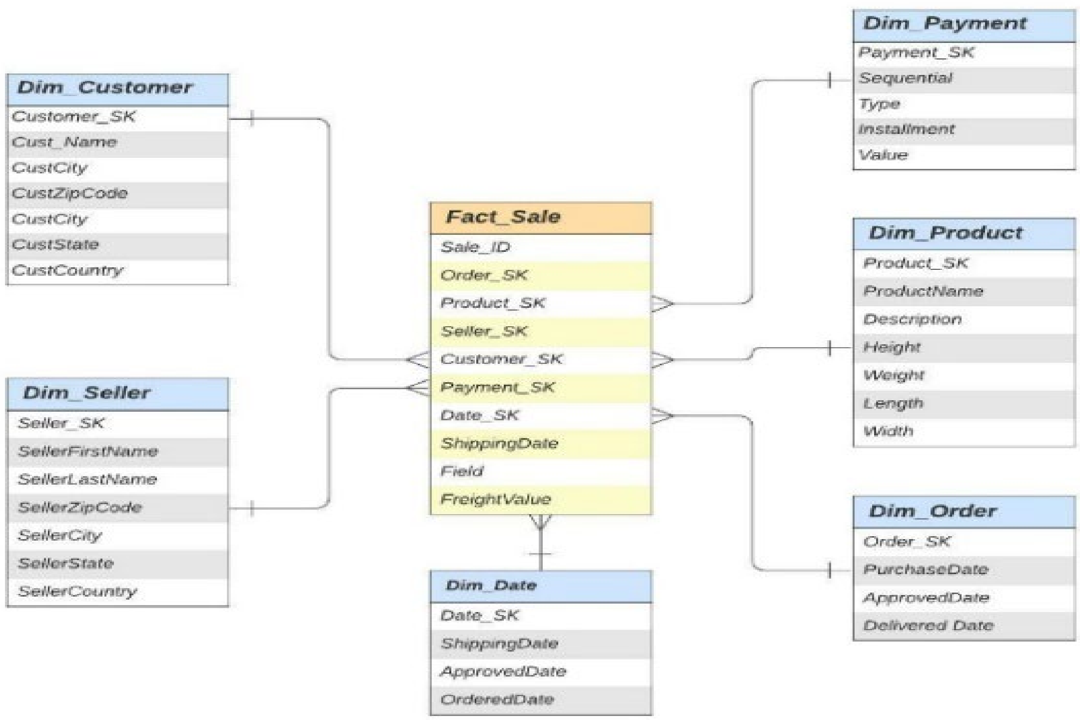

Fig. 6 Proposed Design for the Data Warehouse

From this, it can be deduced that the fact and dimension tables have been derived. The data warehouse includes one sales fact table and six-dimension tables, namely: Customer, Product, Seller, Order, Payment, and Date. During this process, it was observed that the database contains information related to two distinct dates: the order date and the shipment date.

B. ETL Load and Process

Implementing a data warehouse is not always feasible in every scenario. At a smaller scale, retrieving all source data directly and quickly may be more practical. When data is stored separately from business processes, the ETL (Extract, Transform, Load) process can stage and transform it after extracting it from the transactional databases.

Once transformed, the data progresses to the next ETL stage, making it ready for use [22].

In the context of an online store data warehouse for a small and medium-sized enterprise (SME), financial system data may need to be extracted more frequently than data from a CRM system, which typically involves a smaller database. ETL processes become simpler when data is maintained outside the transactional system. Rather than obscuring the data, a robust ETL framework-though potentially resource-intensive-ensures higher transparency and reliability for users.

In some implementations, random ETL processes store data in temporary tables that resemble source data structures. During staging, ETL also handles data transformation and error correction. After these steps are completed, the data is loaded into the data warehouse's dimension and fact tables [23].

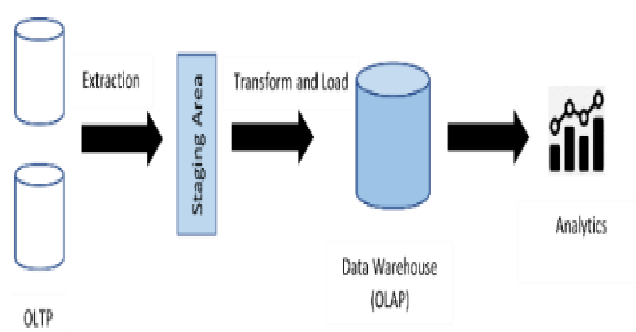

Fig. 7 The Process of Extraction, Transform & Loading

XI. RESULTS AND DISCUSSION

As a result, all data was successfully loaded into Power BI, and several key business questions were effectively addressed. These included: state-wise sales, forecasting future product/category demand, location-based customer purchasing behavior, daily and monthly sales trends, minimum stock levels, cost of goods sold, and profit margins.

Although the model is not limited to answering only the questions listed above, these represent the primary analytical objectives addressed during the evaluation. A well-designed and carefully implemented model provides comprehensive insights into the company's current position and supports critical strategic decision-making to maintain a competitive advantage within the industry.

Fig.8 illustrates an example of a visual report generated using Power BI, specifically addressing the question of which state yields the highest profitability for the business.

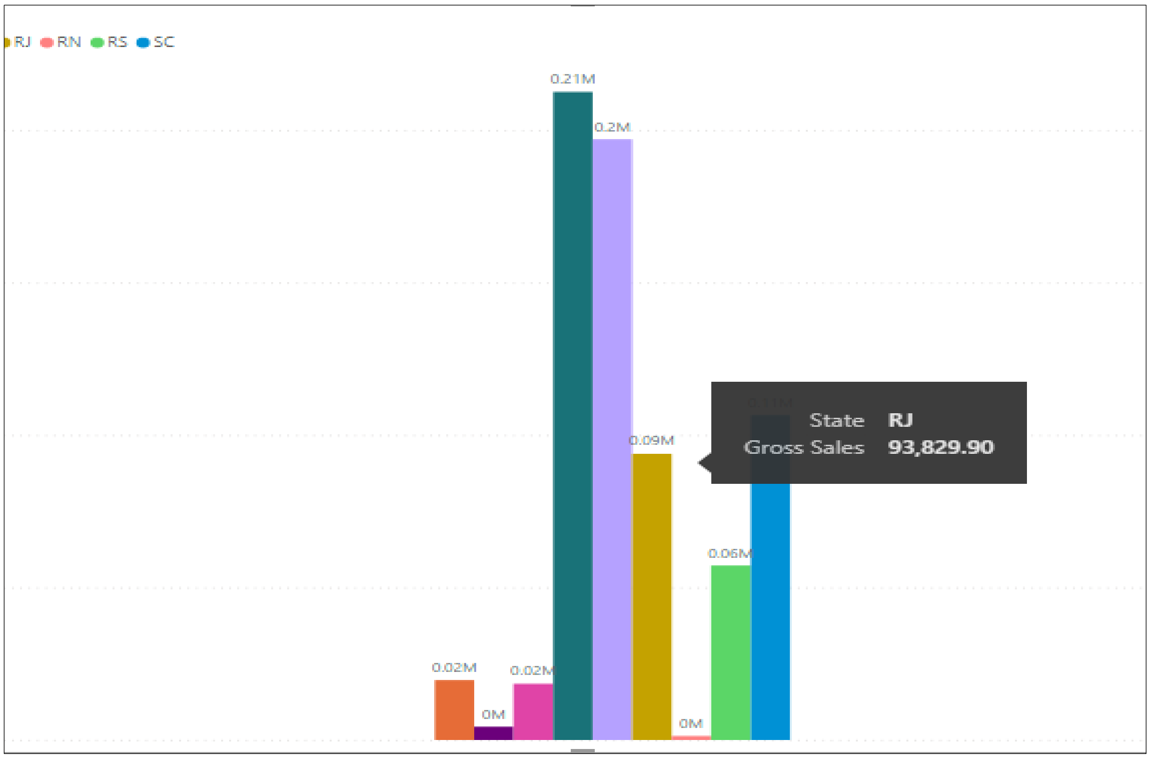

Fig. 8 State based gross sales

It is evident that the state of MG records the highest number of sales, while the state of BA has sales figures that are relatively close to those of PR, but significantly lower than MG's. This analysis provides decision-makers with clear, actionable insights-such as whether to continue operations in the state of BA or consider reallocating resources to states with higher sales potential.

This example illustrates how well-planned and effectively implemented data analytics can provide a company with a strategic advantage, enabling sustained profitability and competitive positioning in the market.

XII. CONCLUSION

The successful implementation of a data warehouse (DW) requires strong organizational support. An SME data warehouse performs most effectively when it incorporates modern data modeling techniques and well-researched best practices-principles that serve as the foundation of DW initiatives globally.

Corporate reporting and dashboards now provide significantly improved reporting capabilities compared to traditional ad hoc queries or basic reporting tools. Enhanced tools allow for more structured analysis, including real-world applications such as building a data warehouse for small and medium-sized enterprises and optimizing query performance.

In this study, the design and implementation of a small enterprise data warehouse demonstrated how star schemas can be efficiently constructed using a well-organized ETL process on a transactional database with multiple sources. A comparison of query performance revealed that the structured star schema within the data warehouse returned results more quickly than the transactional database.

These real-world findings and design insights highlight the substantial benefits that a data warehouse–based reporting system can provide for online retail businesses.

XIII. LIMITATIONS AND FUTURE WORKS

First, the proposed system aims to reduce query and response times for improved performance. The Star Schema is preferred over the Snowflake Schema due to its denormalized and adaptable structure, which makes it easier for small businesses to implement. Queries in a Star Schema are simpler and easier to understand, whereas queries in a Snowflake Schema are more complex due to the multiple foreign key joins across dimension tables. As a result, the Star Schema demonstrates superior performance. Second, while normalization reduces the number of joins in the Star Schema, existing research and literature indicate that small businesses remain hesitant to adopt data warehouses despite their advantages. Future research should explore conventional, innovation, technology acceptance, and knowledge management models to better understand the challenges and concerns small enterprises face in adopting analytical data warehousing solutions. Third, in this study, software tools suitable for a limited number of users were employed. Compared to other office automation technologies, analytics remains underutilized in small enterprises. Training providers could address this gap by offering short courses on how to use Power BI effectively for small business applications.

Declaration of Conflicting Interests

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

Use of Artificial Intelligence (AI)-Assisted Technology for Manuscript Preparation

The authors confirm that no AI-assisted technologies were used in the preparation or writing of the manuscript, and no images were altered using AI.

REFERENCES

[1] M. D. AL-Shboul, “Towards better understanding of determinants logistical factors in SMEs for cloud ERP adoption in developing economies,” *Business Process Management Journal*, vol. 25, no. 5, pp. 887-907, Aug. 2019.

[2] M. Saratchandra and A. Shrestha, “The role of cloud computing in knowledge management for small and medium enterprises: a systematic literature review,” *Journal of Knowledge Management*, vol. 26, no. 10, pp. 2668-2698, Nov. 2022.

[3] S. M. Hånell, E. Rovira Nordman, D. Tolstoy, and N. Özbek, “It’s a new game out there: e-commerce in internationalising retail SMEs,” *International Marketing Review*, vol. 37, no. 3, pp. 515-531, Jul. 2020.

[4] T. Kelepouris, K. Pramatari, and G. Doukidis, “RFID-enabled traceability in the food supply chain,” *Industrial Management & Data Systems*, vol. 107, no. 2, pp. 183-200, Mar. 2007.

[5] K. Ngcobo, S. Bhengu, A. Mudau, B. Thango, and M. Lerato, “Enterprise data management: Types, sources, and real-time applications to enhance business performance-a systematic review,” *Systematic Review*, vol. 26, Sep. 2024.

[6] S. Shargunam and G. Rajakumar, “Predictive analysis on sensor data using distributed machine learning,” *Asian Journal of Computer Science and Technology (AJCST)*, vol. 11, no. 1, pp. 1-4, Jan. 2022.

[7] A. Martins, P. Martins, F. Caldeira, and F. Sá, “An evaluation of how big-data and data warehouses improve business intelligence decision making,” in *Proc. World Conf. Inf. Syst. Technol.*, Springer, Cham, pp. 609-619, Apr. 2020.

[8] R. K. Singh, S. Luthra, S. K. Mangla, and S. Uniyal, “Applications of information and communication technology for sustainable growth of SMEs in India food industry,” *Resources, Conservation and Recycling*, vol. 147, no. 1, pp. 10-18, Aug. 2019.

[9] R. Vasumathi and S. Murugan, “Mining of high average-utility pattern using multiple minimum thresholds in big data,” *Asian Journal of Computer Science and Technology (AJCST)*, vol. 8, no. S2, pp. 57-60, Mar. 2019.

[10] E. Ayoubi and S. Aljawarneh, “Challenges and opportunities of adopting business intelligence in SMEs: collaborative model,” in *Proc. 1st Int. Conf. Data Sci., E-Learning Inf. Syst.*, pp. 1–5, Oct. 2018.

[11] N. AlQershi, S. S. Mokhtar, and Z. Abas, “The influence of structural capital on the relationship between CRM implementation and the performance of manufacturing SMEs,” *Int. J. Syst. Assur. Eng. Manag.*, vol. 13, no. 3, pp. 1205-1218, Jun. 2022.

[12] O. I. Tawfik, O. Durrah, K. Hussainey, and H. E. Elmaasrawy, “Factors influencing the implementation of cloud accounting: evidence from small and medium enterprises in Oman,” *J. Sci. Technol. Policy Manag.*, Jul. 2022.

[13] C. M. Olszak and E. Ziemb, “Critical success factors for implementing business intelligence systems in small and medium enterprises on the example of upper Silesia, Poland,” *Interdisciplinary Journal of Information, Knowledge, and Management*, vol. 129, no. 7, 2012.

[14] W. Noonpakdee, A. Phothichai, and T. Khunkornsiri, “Big data implementation for small and medium enterprises,” in *Proc. 2018 Wireless Opt. Commun. Conf. (WOCC)*, IEEE, pp. 1-5, Apr. 2018.

[15] V. Cherapanukorn, G. Suriyamanee, and S. Wanchaem, “Enterprise resources planning framework for Thai agriculture SMEs,” in *Proc. 2022 Joint Int. Conf. Digital Arts, Media Technol. with ECTI Northern Sect. Conf. Electr., Electron., Comput. Telecommun. Eng. (ECTI DAMT & NCON)*, IEEE, pp. 41-45, Jan. 2022.

[16] R. Kimball and M. Ross, *The Data Warehouse Toolkit: The Complete Guide to Dimensional Modeling*, John Wiley & Sons, 2011.

[17] Kaggle, “Kaggle,” [Online]. Available: https://www.kaggle.com/datasets.

[18] SQL Server, “microsoft.com,” [Online]. Available: https://www.microsoft.com/en-us/sql-server/sql-server-downloads.

[19] PowerBI, “powerbi.microsoft.com,” [Online]. Available: https://powerbi.microsoft.com/en-au/.

[20] M. Patel and D. B. Patel, “Data warehouse modernization using document-oriented ETL framework for real-time analytics,” in *Rising Threats in Expert Applications and Solutions 2022*, Springer, Singapore, pp. 33-41, 2022.

[21] G. Thangarasu, P. Dominic, M. C. Johnwiselin, and S. P. Pradeep Kumar, “Fashions in data mining and hidden knowledge innovation from clinical database,” *Asian Journal of Computer Science and Technology (AJCST)*, vol. 1, no. 2, pp. 36-39, Nov. 2012.

[22] V. Saraswathi Bai, “Data mining methods for communication technology,” *Asian Journal of Computer Science and Technology (AJCST)*, vol. 8, no. S3, pp. 30-34, Apr. 2019.

[23] S. Balamurugan and A. B. Arockia Christopher, “Data pre-processing for classification and clustering,” *Asian Journal of Computer Science and Technology (AJCST)*, vol. 1, no. 1, pp. 1-5, May 2012.