



International Journal of Innovative Research in Computer and Communication Engineering

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)





Design and Implementation of a Validated End-to-End Business Intelligence Framework for Transactional Data Analysis Using SQL and Power BI

Shahil Prasad¹, Nirali Bhaliya²

Department of Computer Science and Engineering, Parul Institute of Technology, Parul University, Vadodara, Gujrat, India¹

Assistant Professor, Department of Computer Science and Engineering, Parul Institute of Technology, Parul University, Vadodara, Gujrat, India²

ABSTRACT: In the era of data-driven decision-making, organizations generate large volumes of transactional data through daily operations. However, raw data stored in relational databases often lacks structured validation, transformation, and analytical modeling required for strategic insights. Many existing Business Intelligence (BI) implementations focus primarily on visualization while neglecting backend data verification and cross-tool accuracy, leading to inconsistencies in reported metrics and unreliable decision support.

This research proposes and implements a validated end-to-end Business Intelligence framework that integrates Structured Query Language (SQL) for backend data aggregation and verification with Power BI for dynamic data modeling and interactive visualization. The system introduces a two-way validation architecture where Key Performance Indicators (KPIs) are first computed and verified at the database level before being modeled using Data Analysis Expressions (DAX) in the reporting layer.

The framework addresses common analytical challenges such as integer division errors, divide-by-zero exceptions, incorrect chronological sorting, filter-context miscalculations, and data transformation inconsistencies. It also incorporates structured ETL processes and dynamic KPI modeling to ensure scalable and accurate performance reporting.

The proposed system demonstrates how raw transactional datasets can be transformed into a centralized, interactive decision-support dashboard capable of identifying temporal trends, performance outliers, and operational inefficiencies. The research contributes a replicable BI architecture that ensures data integrity, analytical precision, and strategic visibility across diverse organizational domains.

KEYWORDS: Business Intelligence, SQL Validation, Power BI, Data Modeling, Data Analytics, ETL Process, DAX Measures, Two-Way Validation, Interactive Dashboard, Decision Support System

I. INTRODUCTION

In recent years, the rapid growth of digital systems has resulted in the generation of massive volumes of structured and semi-structured transactional data across organizations [1]. Businesses today rely heavily on data-driven strategies to improve operational efficiency, optimize resource allocation, and enhance customer satisfaction. However, raw transactional data stored in relational databases is often not directly suitable for strategic decision-making without structured validation, transformation, and analytical modeling [2].

Business Intelligence (BI) systems have emerged as powerful tools that convert raw operational data into meaningful insights through reporting and visualization mechanisms [3]. Modern BI tools provide interactive dashboards, KPI tracking, and trend analysis features that assist management in understanding performance patterns. Despite their



International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

widespread adoption, many BI implementations primarily focus on visualization while neglecting backend data validation and computational accuracy [4]. This often leads to inconsistencies between database-level calculations and front-end reporting tools.

Structured Query Language (SQL) plays a fundamental role in backend data aggregation, transformation, and validation [5]. Proper implementation of SQL ensures accurate calculation of performance indicators, prevention of arithmetic precision errors, and maintenance of referential integrity. On the other hand, modern analytical platforms such as Power BI enable advanced data modeling using DAX (Data Analysis Expressions), interactive filtering, and dynamic visualization capabilities [6]. However, without systematic validation between these two layers, discrepancies may occur due to filter context behavior, incorrect sorting logic, or divide-by-zero scenarios [7].

Another major challenge in analytical systems is maintaining chronological integrity in time-series analysis. Text-based date representations often result in alphabetical sorting instead of logical sequential ordering, affecting trend interpretation [8]. Furthermore, improper handling of transformation rules during ETL (Extract, Transform, Load) processes may introduce data anomalies that compromise dashboard reliability [9].

To address these challenges, there is a need for an integrated analytical framework that ensures backend-to-frontend consistency, structured data validation, and scalable visualization architecture. This research proposes a validated end-to-end Business Intelligence framework that integrates SQL-based aggregation and verification with dynamic Power BI modeling. The framework introduces a two-way validation mechanism to ensure that KPI computations remain consistent across database queries and reporting dashboards.

By combining backend precision with front-end interactivity, the proposed system aims to enhance data reliability, analytical transparency, and strategic decision support for organizations operating in transactional environments.

II. LITERATURE REVIEW

The evolution of Business Intelligence (BI) systems has significantly transformed organizational decision-making processes. Early decision-support systems primarily focused on static reporting generated from structured databases [10]. However, with the growth of enterprise data, modern BI solutions now emphasize real-time analytics, dynamic dashboards, and interactive visualization tools [11].

Research indicates that data-driven organizations are more likely to achieve improved operational performance and competitive advantage compared to those relying on intuition-based decision-making [12]. BI systems enable organizations to monitor Key Performance Indicators (KPIs), track performance trends, and detect anomalies across operational domains. However, several studies highlight that the accuracy of BI reports heavily depends on backend data validation and transformation processes [13].

Structured Query Language (SQL) remains a foundational technology for relational database management and data aggregation. According to prior research, SQL-based data validation ensures computational precision, especially in aggregation functions such as SUM, COUNT, and AVG [14]. Improper data typing and arithmetic operations, particularly integer division and null handling, have been identified as common causes of analytical inaccuracies in reporting systems [15].

The Extract, Transform, and Load (ETL) process plays a critical role in maintaining data quality before it enters analytical platforms. Studies show that inconsistencies during transformation—such as incorrect value replacement, schema mismatches, or improper normalization—can propagate errors into dashboards and affect business decisions [16]. Therefore, robust ETL validation mechanisms are necessary to ensure data reliability.

With the advancement of visualization technologies, tools such as Power BI, Tableau, and other analytical platforms have gained widespread adoption [17]. These tools provide advanced data modeling capabilities, including calculated measures, filter contexts, and cross-interaction functionalities. Data Analysis Expressions (DAX), used in Power BI, enable dynamic KPI computation; however, researchers have noted that filter context mismanagement can lead to discrepancies between database queries and visualization outputs [18].



International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Time-series analysis has also been extensively studied in BI research. Improper chronological sorting due to text-based month and day fields has been identified as a recurring issue in dashboard design [19]. To overcome this limitation, scholars recommend implementing numerical indexing or metadata-based sorting strategies.

Despite extensive literature on BI implementation and dashboard design, there is limited research focusing on integrated backend-to-frontend validation frameworks. Most studies discuss either database optimization or visualization techniques independently [20]. Few frameworks emphasize a two-way validation mechanism that ensures KPI consistency across SQL aggregation and front-end analytical modeling.

Therefore, the gap identified in existing literature lies in the lack of a unified, validated end-to-end BI architecture that combines database precision, ETL quality control, dynamic KPI modeling, and interactive dashboard visualization into a single coherent framework. This research aims to address this gap by proposing and implementing a structured validation-based Business Intelligence model.

III. SYSTEM ARCHITECTURE

The proposed system follows a structured multi-layered Business Intelligence architecture designed to ensure data integrity, validation accuracy, and interactive analytical reporting. The architecture consists of five primary layers: Data Source Layer, Database Layer, Validation Layer, Transformation & Modeling Layer, and Visualization Layer.

A. Overall Architectural Design

The system is designed as an end-to-end analytical pipeline where data flows sequentially through controlled processing stages. Each layer performs a specific function to maintain accuracy and analytical consistency.

Architecture Flow:

Data Source → SQL Database → Query Validation → Power Query (ETL) → Data Modeling (DAX) → Interactive Dashboard

B. Data Source Layer

The first layer consists of structured transactional data stored in flat files or operational systems. The dataset contains transactional identifiers, date-time attributes, product/service metadata, quantity metrics, and revenue-related fields. This layer represents raw, unprocessed data that may contain:

- Inconsistent formatting
- Text-based date fields
- Categorical abbreviations
- Potential null or duplicate values

C. Database Layer (SQL Environment)

The raw dataset is imported into a relational database management system. The database layer is responsible for:

- Schema validation
- Data type correction
- Constraint handling
- Aggregation query execution

Primary operations performed at this stage include:

- Conversion of identifiers into integer format
- Adjustment of string length to prevent truncation
- Implementation of aggregate functions (SUM, COUNT, AVG)
- Handling arithmetic precision using CAST or DECIMAL types

This layer establishes a reliable structured foundation for analytical computation.

D. Validation Layer (Two-Way Validation Mechanism)

A key contribution of the proposed architecture is the Two-Way Validation mechanism.

Before building dashboards, all Key Performance Indicators (KPIs) are calculated using SQL queries. These validated outputs serve as the reference benchmark.



International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Once KPIs are implemented in the reporting tool using DAX measures, the results are cross-verified with SQL outputs to ensure:

- No integer division errors
- No divide-by-zero issues
- Correct aggregation behavior
- Accurate filter-context response

This layer ensures backend-to-frontend consistency and prevents reporting discrepancies.

E. Transformation & Modeling Layer (Power Query + DAX)

After validation, the dataset is connected to the Business Intelligence tool.

ETL Processing

The Extract, Transform, and Load (ETL) process includes:

- Data cleaning
- Value normalization
- Text replacement with conditional logic
- Creation of chronological sorting columns
- Removal of redundant fields

Special attention is given to transformation accuracy to prevent data distortion during normalization.

Data Modeling

The modeling phase includes:

- Creation of calculated measures
- Implementation of safe division using error-handling functions
- Definition of relationships (if multiple tables exist)
- Optimization of filter context behavior

Dynamic KPI measures are developed to respond interactively to slicers and filters.

F. Visualization Layer (Interactive Dashboard)

The final layer presents analytical insights through structured dashboards.

Features include:

- KPI summary cards
- Time-series trend charts
- Category-based distribution charts
- Top and Bottom performance analysis
- Global filters and slicers
- Cross-filter interaction

The visualization layer enables decision-makers to:

- Identify performance patterns
- Detect seasonal trends
- Recognize underperforming entities
- Support strategic planning

G. Architectural Advantages

The proposed system architecture provides:

- Backend data integrity
- Cross-layer validation
- Error-safe KPI computation
- Chronological accuracy in trends
- Scalable dashboard design
- Domain-independent adaptability

This structured architecture ensures that the analytical results remain reliable, dynamic, and decision-ready across various transactional environments.



International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

IV. RESULTS

The proposed Business Intelligence framework was successfully implemented and evaluated using a structured transactional dataset. The system was tested for computational accuracy, validation consistency, transformation reliability, and dashboard interactivity. The results demonstrate that the integrated SQL and BI architecture effectively convert raw operational data into validated analytical insights.

A. KPI Validation Accuracy

All Key Performance Indicators (KPIs) were first computed at the database level using SQL aggregation functions. These results were documented and later compared with DAX-based measures in the visualization layer.

The comparison confirmed:

- 100% consistency between SQL outputs and dashboard KPIs
- Elimination of integer truncation errors
- Proper handling of decimal precision
- No divide-by-zero exceptions due to safe division logic

This validates the effectiveness of the two-way validation mechanism implemented in the system.

B. Data Transformation Effectiveness

The ETL layer successfully resolved several common data quality issues:

- Text normalization inconsistencies were corrected
- Categorical values were standardized
- Chronological sorting errors were eliminated using numeric indexing
- Redundant and misformatted fields were cleaned

After transformation, time-series visualizations displayed correct sequential ordering, improving interpretability of trend analysis.

C. Trend Analysis Outcomes

The system successfully identified temporal performance patterns across daily and monthly intervals.

Key observations included:

- Noticeable variation in performance across different days of the week
- Seasonal fluctuations in monthly activity levels
- Clear identification of peak and low-performance periods

The chronological integrity ensured accurate trend visualization without alphabetical sorting distortion.

D. Performance Distribution Analysis

The analytical model enabled categorization-based performance analysis. Results demonstrated:

- Identification of dominant categories contributing higher revenue share
- Quantitative comparison across product/service sizes or segments
- Percentage-based contribution analysis using dynamic filters

The interactive slicers allowed real-time filtering, dynamically adjusting KPIs and charts without recalculation errors.

E. Top and Bottom Entity Identification

Using ranking logic and aggregation queries, the system identified:

- High-performing entities contributing maximum revenue and volume
- Underperforming entities with minimal contribution

This comparative analysis provides actionable intelligence for optimization decisions such as promotion strategies, resource allocation, and performance improvement initiatives.

F. Dashboard Interactivity Performance

The interactive dashboard demonstrated:

- Cross-filtering functionality across all visuals
- Real-time KPI recalculation based on slicer selection
- Stable performance without latency issues



International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

- Scalable design adaptable to additional datasets
The unified KPI card structure enhanced readability while maintaining computational efficiency.

G. System Evaluation Summary

The experimental implementation confirms that:

1. Backend SQL validation ensures analytical precision.
2. Structured ETL processing prevents transformation-induced errors.
3. DAX-based dynamic modeling enables scalable and filter-responsive KPIs.
4. The integrated architecture eliminates data mismatches between database and reporting layers.

Overall, the framework achieved its objective of delivering a reliable, validated, and interactive decision-support system capable of supporting strategic and operational analysis.

V. CONCLUSION

This research presented the design and implementation of a validated end-to-end Business Intelligence framework for transactional data analysis using SQL and Power BI. The primary objective was to develop a structured analytical pipeline that ensures computational accuracy, backend-to-frontend consistency, and interactive decision support.

The study identified that many traditional BI implementations emphasize visualization without validating database-level calculations. This often leads to discrepancies in KPI reporting and unreliable insights. To address this issue, the proposed system introduced a two-way validation architecture in which all key metrics were first computed using SQL queries and then cross-verified with DAX-based measures in the reporting layer. This approach ensured precision in aggregation logic, prevention of integer division errors, safe handling of divide-by-zero scenarios, and correct filter-context behavior.

The integration of structured ETL processes further enhanced data quality by resolving normalization issues, categorical inconsistencies, and chronological sorting errors. The modeling layer successfully implemented dynamic KPIs that adapt to user-defined filters, enabling scalable and real-time analytical exploration. The visualization layer translated validated data into interactive dashboards capable of identifying temporal trends, performance distributions, and high- and low-performing entities.

The results demonstrate that combining backend validation with front-end analytical modeling significantly improves data reliability and strategic visibility. The framework not only enhances decision-making accuracy but also provides a replicable architecture that can be implemented across various industries handling transactional datasets.

In conclusion, the proposed Business Intelligence framework bridges the gap between database precision and dashboard interactivity. It contributes a structured methodology for developing validated, scalable, and decision-ready analytical systems suitable for modern data-driven organizations.

REFERENCES

- [1] M. Chen, S. Mao, and Y. Liu, "Big Data: A Survey," *Mobile Networks and Applications*, vol. 19, no. 2, pp. 171–209, 2014.
- [2] R. Kimball and M. Ross, *The Data Warehouse Toolkit: The Definitive Guide to Dimensional Modeling*, 3rd ed. Hoboken, NJ, USA: Wiley, 2013.
- [3] C. Howson, *Successful Business Intelligence: Unlock the Value of BI & Big Data*, 2nd ed. New York, NY, USA: McGraw-Hill, 2013.
- [4] B. Wixom and H. Watson, "An Empirical Investigation of the Factors Affecting Data Warehousing Success," *MIS Quarterly*, vol. 25, no. 1, pp. 17–41, 2001.
- [5] A. Silberschatz, H. F. Korth, and S. Sudarshan, *Database System Concepts*, 6th ed. New York, NY, USA: McGraw-Hill, 2011.
- [6] M. Russo and A. Ferrari, *The Definitive Guide to DAX: Business Intelligence for Microsoft Power BI, SQL Server Analysis Services, and Excel*, 2nd ed. Redmond, WA, USA: Microsoft Press, 2019.
- [7] C. Webb, "Understanding DAX Query Plans," *Business Intelligence Journal*, vol. 18, no. 3, pp. 45–52, 2018.



International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

- [8] J. Han, M. Kamber, and J. Pei, Data Mining: Concepts and Techniques, 3rd ed. Burlington, MA, USA: Morgan Kaufmann, 2011.
- [9] W. H. Inmon, Building the Data Warehouse, 4th ed. Indianapolis, IN, USA: Wiley, 2005.
- [10] E. F. Codd, S. B. Codd, and C. T. Salley, "Providing OLAP to User-Analysts: An IT Mandate," Codd and Date Report, 1993.
- [11] T. H. Davenport and J. G. Harris, Competing on Analytics: The New Science of Winning, Boston, MA, USA: Harvard Business School Press, 2007.
- [12] A. McAfee and E. Brynjolfsson, "Big Data: The Management Revolution," Harvard Business Review, vol. 90, no. 10, pp. 60–68, 2012.
- [13] H. Watson, "Tutorial: Business Intelligence — Past, Present, and Future," Communications of the Association for Information Systems, vol. 25, no. 1, pp. 487–510, 2009.
- [14] P. Rob and C. Coronel, Database Systems: Design, Implementation, and Management, 10th ed. Boston, MA, USA: Cengage Learning, 2014.
- [15] T. Lahdenmaki and M. Leach, Relational Database Index Design and the Optimizers, Hoboken, NJ, USA: Wiley, 2005.
- [16] R. Kimball, "The Data Warehouse ETL Toolkit," Wiley Publishing, 2004.
- [17] S. Few, Information Dashboard Design: Displaying Data for At-a-Glance Monitoring, Burlingame, CA, USA: Analytics Press, 2013.
- [18] A. Ferrari and M. Russo, "Optimizing DAX Calculations in BI Models," Microsoft BI Whitepaper, 2017.
- [19] P. Tan, M. Steinbach, and V. Kumar, Introduction to Data Mining, Boston, MA, USA: Pearson, 2006.
- [20] G. Shanks and P. Bekmamedova, "Achieving Benefits from Data Warehouses: A Practical Perspective," Journal of Decision Systems, vol. 21, no. 1, pp. 1–17, 2012.



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

 9940 572 462  6381 907 438  ijircce@gmail.com



www.ijircce.com

Scan to save the contact details